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Editor

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This volume represents the proceedings of the Eighth International Workshop on Computer Modeling and Intelligent Systems (CMIS-2025), held in Zaporizhzhia, Ukraine, in May, 2025. It comprises 28 contributed papers that were carefully peer-reviewed and selected from 96 submissions.

Preface

It is my pleasure to present you the proceedings of The Eighth International Workshop on Computer Modeling and Intelligent Systems (CMIS-2025), held in Zaporizhzhia, Ukraine on 5 of May 2025.

The CMIS workshop was held in 2025 for the eighth time at the National University "Zaporizhzhia Polytechnic", which celebrates in 2025 it's 125-th anniversary and is the largest and oldest regional center for science and higher education in the Zaporizhzhia region of South-Eastern Ukraine.

The main purpose of the CMIS-2025 workshop is a discussion of the recent research results in all areas of Computer Sciences and Information Technologies. The workshop is soliciting research papers including, whilst not limited to, the following areas of interest: Artificial Intelligence, Computer Science Methods for Modeling, and Info-Communication Technologies for Data Analysis and Applications for Engineering, Medicine and Education.

The members of the program committee (PC) and the rules for paper selection have been publicly announced on the web page of the workshop (https://www.facebook.com/groups/cmis.workshop). The PC members list also provided after the preface in these proceedings.

The submission of papers to the CMIS-2025 was open worldwide. There CMIS-2025 workshop countries of PC members and authors of submitted papers are: Algeria, Belgium, Canada, Egypt, Germany, India, Israel, Kazakhstan, Kyrgyz Republic, Netherlands, Poland, Portugal, Slovak Republic, Spain, Türkiye, Ukraine, and Vietnam. The number of countries of CMIS-2025 authors and PC members is 17.

The language of CMIS-2025 Workshop is English. The workshop took the form of oral presentations of peer-reviewed regular papers.

The CMIS-2025 Organizing Committee have received 96 paper submissions, out of which 28 were accepted for presentation as a regular papers in the result of reviewing process, where the editor, PC members, external and peer reviewers, who a well-known international scholars-experts in the CMIS-2025 topics, sought to ensure a high scientific level, as well as a high-quality presentation of the selected papers. These papers were published in this volume of CMIS-2025 proceedings.

The workshop would not have been possible without the support of many people. I would like to thank the CMIS-2025 PC Members, organization staff, and external reviewers for their excellent and tireless work. I sincerely wish that all attendees benefited scientifically from the workshop and wish them every success in their research. It is the humble wish of the workshop organizers that the professional dialogue among the researchers, scientists, and engineers continues beyond the event and that the friendships and collaborations forged will linger and prosper for many years to come.

May, 2025

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A modified neuro-fuzzy counterpropagation network and its fast adaptive learning

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Abstract

A neuro-fuzzy counterpropagation network is introduced that employs a modified fuzzy C-means clustering procedure in an online mode, enhancing both learning rate and accuracy while maintaining the same simple architecture as traditional CPN networks. This modification allows handling of overlapping classes, when an observation can belong to multiple classes simultaneously. Consequently, several output layer neurons can be activated at once. An optimized algorithm is introduced for the output layer tuning with a better control over its filtering and following characteristics through the use of a special adjustable parameter. Experiments demonstrate that this innovative approach outperforms traditional counterpropagation networks in various performance metrics.

Keywords

Counterpropagation network, neuro-fuzzy network, overlapping classes, increased learning rate, short training set

1. Introduction

In recent years, artificial neural networks (ANN) have become a popular solution to various information processing challenges. These include tasks such as pattern recognition (classification), clustering, and forecasting (extrapolation). The success of ANNs can be attributed to their ability to approximate complex functions (universal approximation properties) and learn by adjusting their parameters based on optimization procedures.

Deep neural networks (DNNs), a subset of ANNs, have demonstrated remarkable results in solving numerous data analysis problems. However, DNNs also have significant drawbacks. One major limitation is the requirement for large amounts of training data, which may not always be available. Additionally, DNNs can be slow during parameter adjustment in multi-epoch learning mode. DNNs also face challenges when tackling real-time data stream mining tasks under conditions of non-stationarity and limited input information. Similar limitations apply to classic multilayer perceptron (MLP) models trained using the error backpropagation procedure.

It is worth noting that classic radial basis function networks (RBFN) [1, 2] exhibit a higher learning rate but may encounter issues related to the "curse of dimensionality" as the number of input signals increases.

In today's data-driven world, there is a growing need for neural networks that can efficiently handle data stream mining tasks in online mode with limited training data. Among various neural network models, the counterpropagation neural network (CPN), introduced by R. Hecht-Nielsen [3-5], stands out as a viable solution despite its architectural simplicity.

Advantages of CPNs:

- High learning rate: CPNs are known for their ability to learn quickly.
- Simple architecture: only two layers formed by simple nodes, CPNs offer computational efficiency.

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However, there is an inherent trade-off. While CPNs excel in learning rate, their approximation properties – the ability to model complex functions – are inferior compared to traditional MLPs and RBFNs, and of course modern DNNs, which are generally more powerful in function approximation.

Despite these limitations, ongoing research focuses on enhancing the approximation capabilities of CPNs while maintaining their high learning and processing rates. These efforts aim to bridge the gap between performance and efficiency without compromising on speed. Recent applications of CPNs include but are not limited to classification [6-9], prediction [10], parameter identification [11], structural optimization [12], extreme learning machine optimization [13], digital image watermarking [14], navigation systems development [15] and others. One promising direction for improvement involves integrating hybrid systems of computational intelligence [16]. Specifically, neuro-fuzzy approaches, which combine neural networks with fuzzy logic, offer a potential solution. By leveraging these methods [2, 17, 18] it may be possible to enhance the characteristics of CPNs. In conclusion, while CPNs present unique challenges compared to more sophisticated neural architectures like DNNs and MLPs, ongoing research explores innovative solutions that could unlock their full potential.

2. Counterpropagation network basics

From a theoretical point of view, the counterpropagation network is intended for restoring the nonlinear mapping $y=F(x)$ (forward-only CPN architecture shown in Fig. 1 is sufficient), as well as the inverse mapping $x=F^{-1}(y)$ (full CPN architecture is required, see Fig. 2), i.e. identifying a nonlinear transform

$$F: X \to Y\left(R^n \to R^m\right)$$

from the training samples $x(1), y(1), \ldots, x(k), y(k), \ldots, x(N), y(N)$, where $x(k)=\left(x_1(k), \ldots, x_i(k), \ldots, x_n(k)\right)^T \in R^n$, $y(k)=\left(y_1(k), \ldots, y_i(k), \ldots, y_m(k)\right)^T \in R^m$, $k=1,2,\ldots,N$ is the observation index in the dataset, or the index of the current discrete time, if the data is being processed in online mode.

CPN contains two layers of neurons: the first hidden layer, called the T. Kohonen layer, and the output layer, called the S. Grossberg layer. In this paper, we will focus on the forward-only architecture, but the proposed methods are equally applicable to the full CPN architecture as well.

The input signals $x(k)$ arrive sequentially from the receptive layer to the first hidden layer, which is usually a Kohonen's self-organizing map (SOM) [19, 20] designed to solve the crisp clustering problem, i.e. dividing the data set into h non-overlapping classes/clusters in the self-learning mode. SOM implements the following "Winner Takes All" mapping

$$u_l(k)=\begin{cases} ¿\, 1, if\ w_l^K(k)\ is\ a\ winner, i.e. \left\|x(k)-w_l^K(k)\right\| \le \left\|x(k)-w_i^K(k)\right\| \ \forall i=1,2,\ldots,h \\ ¿\, 0\ otherwise \end{cases} \quad (1)$$

where $u(k)=\left(u_1(k), \ldots, u_l(k), \ldots, u_h(k)\right)^T$, $W^K=\left\{w_{li}^K\right\}-(h\times n)$ tuned matrix of synaptic weights that define centroids of the clusters.

The Kohonen layer learning is based on the same "Winner Takes All" (WTA) principle, when only one winning neuron is tuned at each iteration $k=1,2,\ldots$ When observation $x(k)$ is received, the closest to $x(k)$ neuron is determined (in the Euclidean metrics sense), which is called a "winner" (1). Then only this "winner" neuron's vector of weights $w_l^K(k)$ is being tuned according to the rule:

$$w_l^K(k+1)=\begin{cases} ¿\, w_l^K(k)+\eta_K(k)\left(x(k)-w_l^K(k)\right), if\ w_l^K(k)\ is\ a\ winner, \\ ¿\, w_l^K(k)\ otherwise \end{cases} \quad (2)$$

(here $0<\eta_K(k)<1$ is the Kohonen layer learning rate parameter, which is usually chosen empirically). Note also that when $\eta_K(k)=k^{-1}$ procedure (2) calculates the arithmetic mean (centroid) of the l^{th} cluster, i.e. it actually implements the popular crisp K-means clustering algorithm.

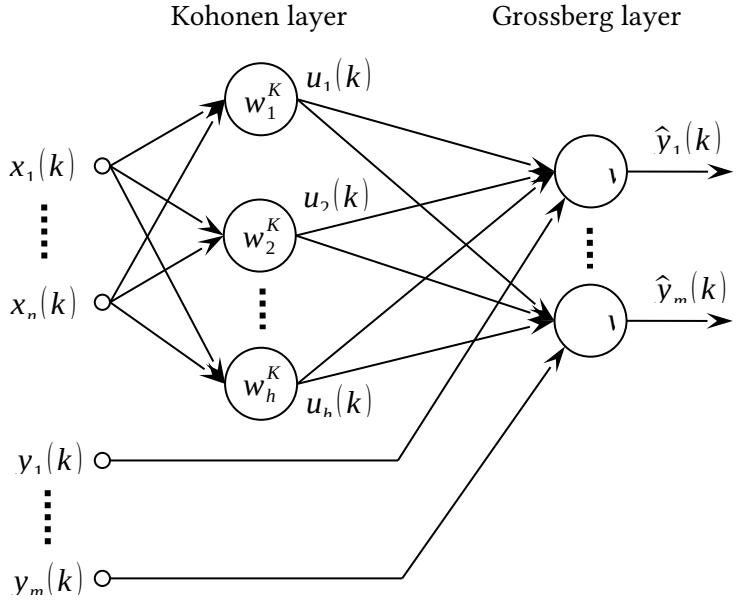

Figure 1: Forward-only counterpropagation network architecture

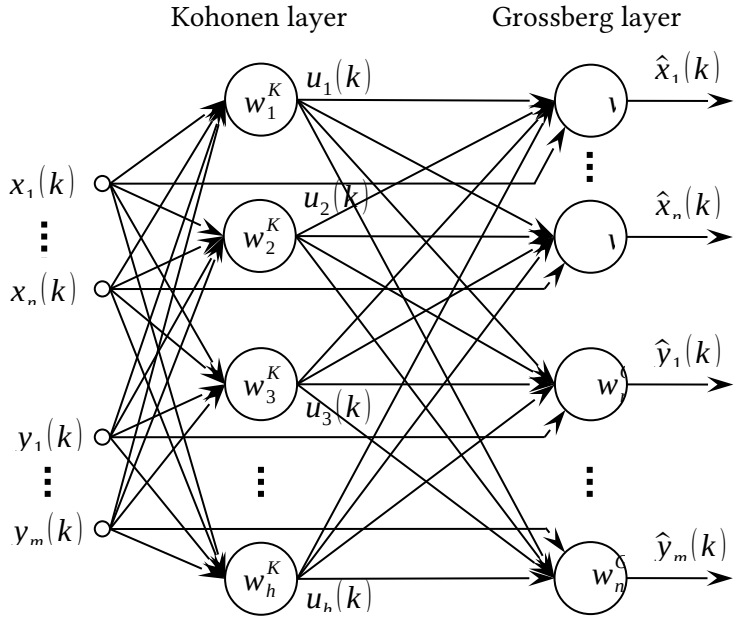

Figure 2: Full counterpropagation network architecture

The output layer is formed by the so-called Grossberg outstars, which are essentially modifications of the standard linear element (Adaline) and implement the mapping

$$\hat{y}(k)=W^G u(k), \tag{3}$$

where $W^G=\{w_{jl}^G\}$ – $(m\times h)$ matrix of synaptic weights tuned in the controlled learning mode.

Outstar neurons of the output (Grossberg) layer are usually trained using a fairly simple algorithm

$$w_{jl}^{G}(k+1)=w_{jl}^{G}(k)+\eta_{G}(k)u_{l}(k)\left(y_{l}(k)-w_{jl}^{G}(k)\right)$$

or using vector notation,

$$w_{j}^{G}(k+1)=w_{j}^{G}(k)+\eta_{G}(k)u^{T}(k)\odot\left(y_{l}(k)E_{h}-w_{l}^{G}(k)\right), \tag{4}$$

where $0<\eta_{G}(k)<1$ is the Grossberg layer learning rate parameter, E_{h} is a $(1\times h)$ vector of ones, $\odot$ is the element-wise product symbol

So, this neural network acts like a simple lookup table. It gives outputs in steps rather than smoothly, which limits its ability to model complex relationships. Furthermore, using a "Winner Takes All" approach in the Kohonen layer means that during training, only one outstar is adjusted at a time. This makes the overall training process slower.

Given these limitations, modifying the Counterpropagation Neural Network along with its learning methods could enhance its ability to model functions more accurately while speeding up the training process.

3. Neuro-fuzzy counterpropagation network (NFCPN)

The proposed NFCPN maintains the same architecture as traditional CPN networks, but introduces key improvements. Instead of employing a traditional Self-Organizing Map within the Kohonen layer, which traditionally uses a recurrent version of the crisp K-means clustering algorithm, our approach utilizes a modified fuzzy C-means clustering procedure (FCM) [21, 22] in the recurrent form [23], enhancing both learning efficiency and approximation accuracy.

This modification allows for effective handling of situations where classes overlap in feature space, enabling an observation to belong to multiple classes simultaneously. Furthermore, by applying a nonlinear strategy, the network can activate several output layer neurons at once. In contrast, classic CPN networks only trigger one Grossberg outstar during learning, which inherently slows down the process.

Overall, these changes significantly improve the network's performance and adaptability in complex scenarios.

3.1. Kohonen layer learning

To improve the quality and speed of the SOM clustering, we use the so-called "Winner Takes More" (WTM) rule, instead of WTA. This approach utilizes a neighborhood function $\psi(l,g,k)$ that determines the proximity of all other neurons $w_{g}^{K}(k), g=1,2,\ldots,l-1,l+1,\ldots,h$ to the "winner" $w_{l}^{K}(k)$. For $g=l$, $\psi(l,l,k)=1$, and the value of $\psi(l,g,k)$ decreases with the increase of the distance between vectors $w_{l}^{K}(k)$ and $w_{g}^{K}(k)$.

All centroids – vectors of synaptic weights are tuned according to the modified learning rule

$$w_{l}^{K}(k+1)=w_{l}^{K}(k)+\eta_{K}(k)\psi(l,g,k)\left(x(k)-w_{l}^{K}(k)\right)\ \forall\, l=1,2,\ldots,h \tag{5}$$

It is readily seen that (5) is a generalization of the WTA algorithm (2), for which the neighborhood function is a singleton. Unfortunately, there are no formal rules for determining neighborhood functions $\psi(l,g,k)$, hence their selection is based on empirical considerations.

Considering a more practical situation, when each observation can belong to several or all clusters simultaneously, it is beneficial to use a recurrent modification of J.C. Bezdek's FCM algorithm [21] related to optimization of the following objective function

$$J\left(\mu_{l}(k),w_{l}^{K}\right)=\sum_{k=1}^{N}\sum_{l=1}^{h}\mu_{l}^{\beta}(k)\left\|x(k)-w_{l}^{K}\right\|^{2}$$

subject to constraints

$$\sum_{l=1}^{h}\mu_l(k)=1\ \forall\, k=1,2,\ldots,N,$$
$$0<\sum_{k=1}^{N}\mu_l(k)<N\ \forall\, l=1,2,\ldots,h.$$

Here $\mu_l(k)$ – degree of fuzzy membership of observation $x(k)$ to l^{th} cluster, $\beta>0$ – fuzzifier (usually $\beta=2$), w_l^K – centroid of l^{th} cluster.

Solving the optimization problem based on finding the saddle point of the Lagrange function

$$L\left(\mu_l(k),w_l^K,\lambda(k)\right)=\sum_{k=1}^{N}\sum_{l=1}^{h}\mu_l^{\beta}(k)\left\|x(k)-w_l^K\right\|^2+\sum_{k=1}^{N}\lambda(k)\left(\sum_{l=1}^{h}\mu_l(k)-1\right) \tag{6}$$

(here $\lambda(k)$ – Lagrange multipliers) for $\beta=2$ leads to the standard FCM algorithm

$$\begin{cases} ¿\,\mu_l(k)=\dfrac{\left\|x(k)-w_l^K\right\|^{-2}}{\sum\limits_{g=1}^{h}\left\|x(k)-w_g^K\right\|^{-2}}, \\ ¿\,w_l^K=\dfrac{\sum\limits_{k=1}^{N}\mu_l^2(k)x(k)}{\sum\limits_{k=1}^{N}\mu_l^2(k)}. \end{cases}$$

To solve the fuzzy clustering problem in online mode, i.e. training the fuzzy Kohonen map, consider a local modification of the Lagrange function (6) in the form [24, 25]

$$L\left(\mu_l(k),w_l^K(k),\lambda(k)\right)=\sum_{l=1}^{h}\mu_l^{\beta}(k)\left\|x(k)-w_l^K(k)\right\|^2+\lambda(k)\left(\sum_{l=1}^{h}\mu_l(k)-1\right).$$

Optimizing it with the K.J. Arrow, L. Hurwitz, H. Uzawa procedure [26], we obtain the following result

$$\begin{cases} ¿\,\mu_l(k)=\dfrac{\left\|x(k)-w_l^K(k)\right\|^{-\beta}}{\sum\limits_{g=1}^{h}\left\|x(k)-w_g^K(k)\right\|^{-\beta}}, \\ ¿\,w_l^K(k+1)=w_l^K(k)+\eta_K(k)\mu_l^{\beta}(k)\left(x(k)-w_l^K(k)\right), \end{cases} \tag{7}$$

which coincides with the D.C. Park, I. Dagher algorithm [27] when $\beta=2$:

$$\begin{cases} ¿\,\mu_l(k)=\dfrac{\left\|x(k)-w_l^K(k)\right\|^{-2}}{\sum\limits_{g=1}^{h}\left\|x(k)-w_g^K(k)\right\|^{-2}}, \\ ¿\,w_l^K(k+1)=w_l^K(k)+\eta_K(k)\mu_l^{2}(k)\left(x(k)-w_l^K(k)\right). \end{cases} \tag{8}$$

It is easy to see that (7), (8) structurally coincide with the WTM algorithm (5), but here the neighborhood function is being chosen automatically.

Next, the calculated membership degrees $\mu_l(k)\ \forall\, l=1,2,\ldots,h$ are fed to the output layer of the network, i.e. vector $u(k)$ is formed not by a single one and a set of zeros, but by membership degrees $\mu_l(k)$, which activate all neurons of the Grossberg output layer.

3.2. Grossberg layer learning

As described above, the Grossberg layer receives the vector $\mu(k)=\left(\mu_1(k),\ldots,\mu_l(k),\ldots,\mu_h(k)\right)^T$ as input, instead of $u(k)$ in classic CPN. This leads to acceleration of the Grossberg layer learning, because all weights are being updated at each iteration, not only the ones connected to the "winner" of the Kohonen layer. Hence, instead of (2), the learning process of this layer can be rewritten as

$$w_j^G(k+1)=w_j^G(k)+\eta_G(k)\mu^T(k)\odot\left(y_l(k)E_h-w_l^G(k)\right). \tag{9}$$

The output layer learning rate parameter $\eta_G(k)$ can be optimized, considering the objective function

$$J\left(w_j^G\right)=\frac{1}{2}\left(y_l(k)-w_l^G\mu(k)\right)^2$$

and its gradient optimization procedure

$$w_j^G(k+1)=w_j^G(k)+\eta_G(k)\left(y_l(k)-w_l^G(k)\mu(k)\right)\mu^T(k). \tag{10}$$

Optimizing (10) for speed leads to the Kaczmarz-Widrow-Hoff algorithm [28-30] in a form

$$w_j^G(k+1)=w_j^G(k)+\frac{y_l(k)-w_l^G(k)\mu(k)}{\left\|\mu(k)\right\|^2}\mu^T(k). \tag{11}$$

The balance between filtering and following properties of (11) can be chosen by the following modification [31, 32]:

$$\begin{cases} ¿\, w_j^G(k+1)=w_j^G(k)+\alpha^{-1}(k)\left(y_l(k)-w_l^G(k)\mu(k)\right)\mu^T(k), \\ ¿\,\alpha(k)=\gamma\alpha(k-1)+\left\|\mu(k)\right\|^2, 0\le\gamma\le 1, \end{cases} \tag{12}$$

which coincides with (11) when $\gamma=0$, and becomes a stochastic approximation procedure when $\gamma=1$.

4. Experimental results

4.1. Experimental setup

For the sake of comparison between classic counterpropagation network (CPN) and the proposed neuro-fuzzy counterpropagation network (NFCPN), we use a simple test case with $n=2$ inputs, $h=9$ neurons in the Kohonen layer, and $m=1$ output. Inputs $x_1(k), x_2(k)$ are sampled from the uniform distribution over the interval $[0,1]$, the corresponding output is calculated as $y(k)=\left(x_1(k)^2+x_2(k)^2\right)^{\frac{1}{2}}$.

The first $N=1000$ observations form the training set, another $T=1000$ observations form the test set. Both networks operate in online mode, processing all N training observations sequentially and only once, updating their parameters after each step k. Also, after each step, the mean absolute error (MAE) is calculated over the entire test set, i.e. we monitor how the out-of-sample error changes during the online training process.

First, both networks are trained under the same conditions $\eta_K(k)=\eta_G(k)=0.1\ \forall k=1,2,\ldots,N$, hence we compare WTA principle in CPN versus WTM in NFCPN (Fig. 3). Then, an optimized learning algorithm (12) with various values of parameter γ is used for NFCPN in order to further improve its performance (Fig. 4). Numerical results are presented in Table 1.

Table 1
Effectiveness comparison

Network type and parameters	MAE = 0.1 at $k=¿$	MAE at $k=1000$
CPN, $\eta_K(k)=\eta_G(k)=0.1$	399	0.085
NFCPN, $\eta_K(k)=\eta_G(k)=0.1$	264	0.065
NFCPN, $\eta_K(k)=0.1, \gamma=0$	23	0.07–0.12
NFCPN, $\eta_K(k)=0.1, \gamma=0.9$	118	0.065
NFCPN, $\eta_K(k)=0.1, \gamma=0.99$	695	0.081
NFCPN, $\eta_K(k)=0.1, \gamma=1.0$	–	0.184

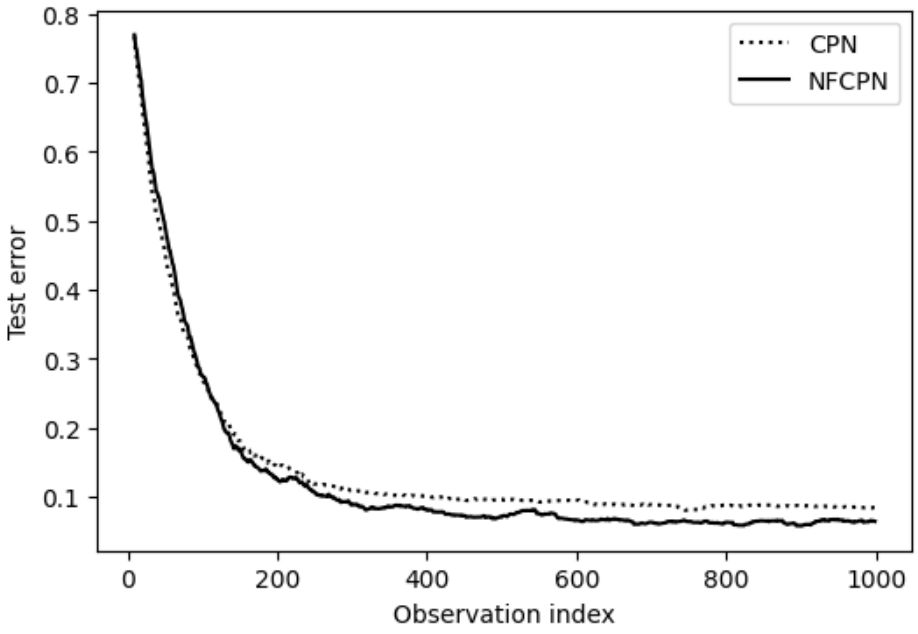

Figure 3: CPN vs NFCPN errors

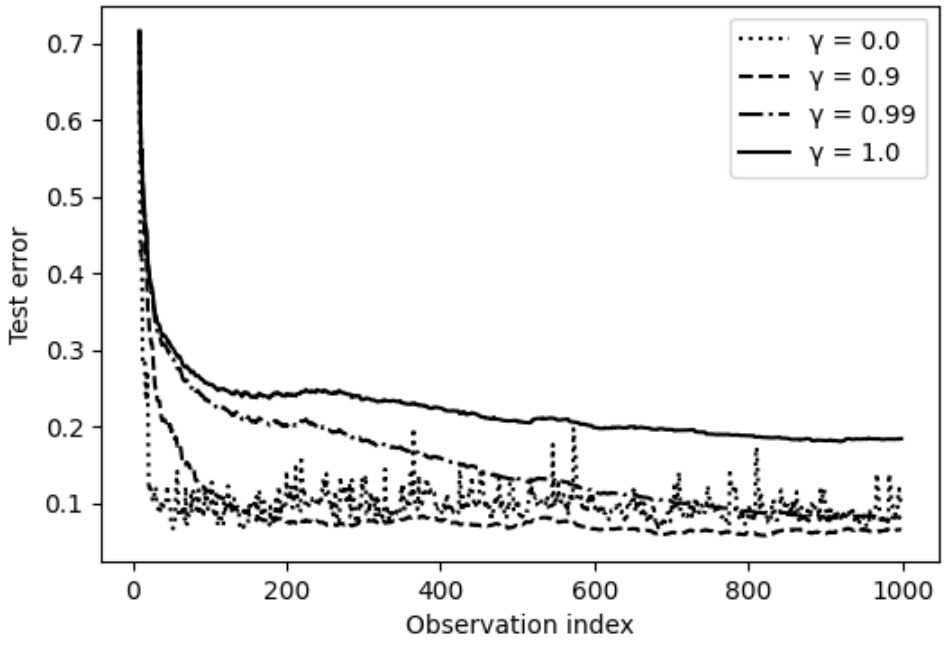

Figure 4: NFCPN errors at different levels of γ

The analysis conducted on the results reveals significant differences between traditional counterpropagation networks (CPN) and neuro-fuzzy counterpropagation networks (NFCPN). These findings highlight the advantages of using NFCPN in achieving faster learning rates and improved accuracy.

4.2. Learning efficiency: MAE comparison across networks

Mean Absolute Error (MAE), a key metric for evaluating model performance, was calculated at various stages of training. The results demonstrate that:

- Classic CPN: At $k=399$ iterations, the classic CPN achieved MAE level of 0.1.
- NFCPN: In comparison, the neuro-fuzzy counterpart reached a similar MAE level of 0.1 at $k=264$ iterations.

This indicates that NFCPN requires fewer training cycles to achieve comparable accuracy, suggesting superior learning efficiency compared to classic CPN. Further results reinforce this conclusion.

At $k=1000$:

- Classic CPN: The MAE stabilized at 0.085.
- NFCPN: Achieved an improved MAE of 0.065, showcasing greater accuracy even as training progressed.

These results collectively demonstrate that, with the same training parameters, NFCPN learns approximately 1.5 times faster than CPN and is by 24% more accurate in performing the given task.

4.3. Adjusting learning dynamics: the role of gamma parameter (γ)

The study also explored different configurations for enhancing learning performance using algorithm (12) and adjusting the gamma parameter (γ).

Initially, γ was set to 0. This setting significantly increased the learning rate by over 10 times in comparison to the classical learning algorithm with $\eta_K(k)=\eta_G(k)=0.1$. However, this improvement came at a cost – training became noisy, lacking effective filtering properties. To address this trade-off and improve the filtering characteristics of the algorithm without compromising learning speed, gamma was gradually increased. With $\gamma=0.9$, errors comparable to those achieved with a fixed $\eta_G(k)=0.1$ were observed. Additionally, this configuration maintained an impressive learning rate that was about 2.2 times faster than with the classical learning algorithm.

This experimentation underscores the importance of fine-tuning gamma to achieve a balance between noise reduction and efficient learning rates. By carefully controlling gamma, it is possible to optimize both filtering properties and following characteristics (i.e., adaptability to changes in non-stationary data streams).

4.4. Key findings summary

- Learning rate: NFCPN consistently outperforms CPN by achieving comparable or better MAE with fewer training iterations.
- Accuracy enhancement: The improved performance of NFCPN results in a 24% increase in accuracy over classic CPN under the same conditions.
- Parameter optimization: Modifying gamma allows for precise control over learning dynamics, balancing between noisy and stable training processes. Adjusting gamma to higher values enhances filtering properties without significantly compromising on learning speed.

5. Conclusions

We have introduced a fuzzy modification to a counterpropagation network, enhancing its ability to handle situations where data categories overlap. This means an item can belong to multiple classes simultaneously, which is common in real-world scenarios.

Our modifications improve the network's learning efficiency and enable it to address a wider range of problems in real-time data processing. Additionally, this enhanced version is simpler mathematically and requires less training data compared to traditional methods. It also adapts smoothly as new, varied data arrives, which is crucial for handling dynamic information streams.

Experiments demonstrate that our modified network performs effectively and outperforms the standard CPN model. These results suggest that neuro-fuzzy counterpropagation networks hold significant potential in real-time data processing tasks where both efficiency and accuracy are critical. The ability to adjust gamma parameter offers flexibility, enabling the network to adapt to varying levels of non-stationarity in input data streams.

Further research could explore additional parameter configurations or investigate how the proposed approach generalizes across different tasks. We also aim to explore different clustering techniques within the hidden layer of NFCPN to further enhance its capabilities. Such advancements would likely enhance the applicability of counterpropagation networks across a broader range of real-world scenarios.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Advancing Predictive Control: Insights from Maze Exploration Using Markov Decision Processes

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Abstract

Predictive control plays a significant role in mobile robotics, especially in trajectory tracking, obstacle avoidance, and real-time decision-making. In this study, we explore how Markov Decision Processes (MDPs) can be integrated with predictive control to enhance navigation, particularly in maze-like environments. A case study on MDP-based maze exploration analyzes key system limitations, including computational complexity and real-time adaptability. While MDPs often struggle to adapt to dynamic environments, predictive techniques like Model Predictive Control (MPC) offer improvements in trajectory optimization and responsiveness. We also discuss practical applications in areas such as warehouse navigation and multi-robot coordination, showing the benefits of combining MDPs and predictive control for robust performance in real-world scenarios.

Keywords

Predictive Control, Markov Decision Processes, Maze Exploration, Mobile Robots, Trajectory Tracking

1. Introduction

Autonomous navigation is a fundamental capability in mobile robotics, allowing robots to traverse complex and dynamic environments efficiently. Achieving accurate trajectory tracking and efficient maze exploration is still challenging due to uncertainties in the environment, sensor limitations, and computational constraints. Addressing these challenges requires robust decision-making frameworks and control techniques.

Predictive control techniques, particularly Model Predictive Control (MPC), have demonstrated significant advantages in trajectory tracking and obstacle avoidance by enabling real-time adjustments based on predicted future states [1,2]. Its structured approach has seen success in autonomous driving, industrial automation, and robotic path planning, offering a structured approach to real-time motion optimization while ensuring the satisfaction of the constraints. In parallel, Markov Decision Processes (MDPs) offer a robust mathematical foundation for decision-making under uncertainty, widely applied in navigation and mapping tasks [3,4].

Successes of MDPs and MPC are well documented, but their integration in mobile robotics is still underexplored. Existing studies primarily focus on standalone MDPs for decision-making or MPC for trajectory optimization, yet few works have attempted to bridge the gap between these two methods. Most of the literature on MDPs addresses static environments with predefined state transitions, limiting their real-time adaptability. Although MPC offers dynamic control it lacks the high-level policy optimization capabilities of MDPs. To overcome the limitations, the article examines integrating MDPs with predictive control techniques. We aim to combine MDP-based decision-making with the real-time adaptability of MPC to enhance mobile robot trajectory tracking in dynamic and uncertain environments.

This study extends previous work by analyzing the limitations of MDP-based maze exploration and demonstrating how predictive control can address these challenges. We highlight the novelty of our approach by reviewing existing literature and identifying gaps in current research. Researchers have extensively studied individual applications of MDPs and MPC, yet their combined use to enhance real-time adaptability and decision-making in maze exploration remains underexplored.

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Primarily, this article aims to contribute to this area by presenting a structured approach for integrating predictive control with MDP-based systems.

The rest of this paper is structured as follows. Section II reviews related work, analyzing existing MDP and predictive control approaches in mobile robotics. Section III presents the case study, discussing the implementation of MDPs for maze exploration. Section IV explores the integration of predictive control techniques and their impact on real-time navigation. Finally, Section V outlines future research directions and potential improvements in hybrid MDP-MPC frameworks.

2. Background and Related Work

2.1. Markov Decision Processes in Robotics

Markov Decision Processes (MDPs) provide a mathematical framework to model decision-making problems in stochastic environments [1]. An MDP is defined as a tuple (**S**, **A**, **P**, **R**, γ), where:

- **S** is a finite set of states representing the possible configurations of the environment.
- **A** is a finite set of actions available to the agent.
- **P(s′|s, a)** is the state transition probability, which defines the probability of reaching the state.
- **R(s, a)** is the reward function, which assigns a scalar reward to each state-action pair.
- γ ∈ [0,1] is the discount factor, which determines the importance of future rewards.

The objective in an MDP is to find an optimal **policy π(s)**, which maps state to actions to maximize the expected cumulative reward:

$$V^{\pi}(s) = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right],$$

where $V^{\pi}(s)$ is the value function representing the expected reward when following **policy** π from state ***s***. The **optimal policy** $\pi*$ maximizes this value, often computed using **Value Iteration** or **Policy Iteration** algorithms [15]:

$$V^{\pi¿}(s) = \max_{a}\left[\sum_{s'} P(s'|s,a) R(s_t, a_t) + \gamma^t V^{\pi¿}(s')\right].$$

MDPs have been widely used in robotics for path planning, exploration, and navigation [3]. They enable robots to compute optimal policies for sequential decision problems, making them particularly effective for grid-world environments where the system must balance exploration and exploitation.

However, one major limitation of MDPs is their **computational complexity** in real-time applications, especially in large environments. Since MDPs rely on full knowledge of transition probabilities and rewards, they struggle with dynamic environments where state transitions may change unpredictably. This motivates the need for predictive control to enhance real-time adaptability.

2.2. Predictive Control for Mobile Robots

Predictive control, particularly Model Predictive Control (MPC), has emerged as a powerful approach for real-time motion planning and trajectory tracking in robotics [2]. Unlike MDPs, which focus on long-term reward optimization, MPC formulates an optimal control problem over a finite prediction horizon and continuously updates actions based on real-time sensor data.

MPC solves an optimization problem at each time step to minimize a cost function J while satisfying system constraints:

$$J = \sum_{k=0}^{N} \left[x_k^T Q\, x_k + u_k^T R\, u_k\right]$$

where: J is the cost function,
x_k represents the state vector at time step k,
u_k represents the control input at time step k,
Q and R are weight matrices that penalize state deviation and control effort, respectively,
N is the prediction horizon.

Following [14], we adapt the equation for this context.

MPC predicts future states using the system dynamics:

$$S_{e+1} = r\ (S_e, g_e).$$

Subject to constraints:

$$g_{i\ y} \le g_e \le g_{i\ PS},\ S_{i\ y} \le S_e \le S_{i\ PS}.$$

Having a predictive capability allows MPC to dynamically adjust robot actions, making it highly effective for applications such as:

- Obstacle avoidance in dynamic environments [12].
- Multi-robot coordination, ensuring collision-free paths [13].
- Real-time trajectory planning in complex terrains [11].

2.3. Combining MDPs and Predictive Control

Although MDPs provide a structured approach for high-level decision-making, they lack adaptability in real time. While MPC excels at short-term control and constraint handling, it lacks an inherent ability to model long-term decision-making.

Integrating MDPs with MPC leverages the advantages of both:

- MDPs generate an optimal policy for global navigation based on reward optimization.
- MPC executes the policy in real time while adapting to dynamic changes.

Hybrid approach allows for robust decision-making and efficient trajectory execution, particularly in dynamic maze exploration and autonomous navigation scenarios. The following sections explore how this integration can enhance mobile robot performance.

3. Case Study: Maze Exploration with MDPs

3.1. System Description

A mobile robot explores a maze autonomously in a grid world environment, where each cell represents a state. Markov Decision Process (MDP)-based algorithms define the transitions between states, guiding the robot's decision-making [4]. The objective is to enable efficient navigation from a starting position to a goal while avoiding obstacles and optimizing movement based on predefined rewards.

- Hardware Setup: The physical robot consists of different components, as shown in Fig. 1, mainly:
  - Microcontroller: The ESP32 microcontroller processes the MDP algorithm and controls the robot's movement.
  - Sensors:
    1. Ultrasonic sensor: Obstacle detection relies on the HC-SR04 sensor.
    2. Camera module: A separate Sony IMX298 camera module connects to the Raspberry Pi using the MIPI CSI-2 interface, then transmits data to the ESP32 microcontroller via Wi-Fi for processing.

Object detection techniques were employed to distinguish the robot from the environment, and a localization module processed this data for accurate mapping [7].

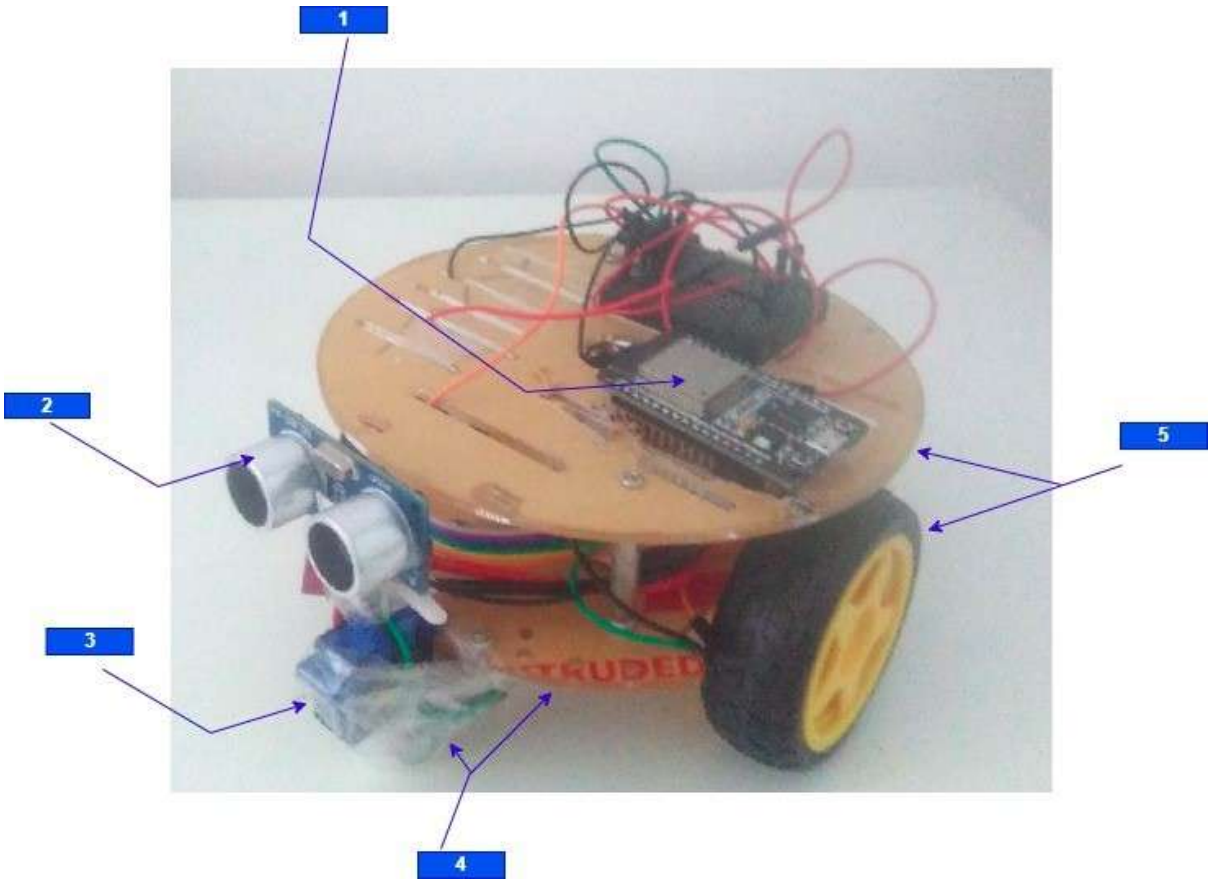

Figure 1: Physical mobile robot used for MDP-based maze exploration. The legend highlights key components: (1) ESP32 o-controller, (2) Ultrasonic-sensor, (3) Servo-motor, (4) Two caster wheels, and (5) Two primary dual shaft DC motor-driven wheels.

- Motors Driver: Dual-shaft DC motors with a motor driver for precise motion control over movement [1]. Along with two caster wheels, a freely rotating wheel supports the robot's weight and enables smooth, multi-directional movement.
- Software Algorithm Implementation:
  – MDP-Based Decision Making: The robot uses an MDP framework to determine optimal actions in each state.
  – Policy Iteration Value Iteration Algorithms: These methods compute the best navigation policy based on state transitions and rewards.
  – Localization Mapping: A vision-based system helps in state estimation and tracking the robot's movement.
  – Combine a left-hand rule maze exploration algorithm to optimize performance and minimize the robot's rotation time.
- Grid-World Representation:

The environment is modeled as a 3x4 discrete grid-world maze with defined start, goal, and obstacle states, as shown in Fig. 2. The goal was to determine an optimal policy for the robot to navigate from the start state to the goal state while avoiding obstacles and maximizing rewards where:

1.Each cell represents a state (position in the maze). * State transitions are probabilistic, accounting for uncertainties in movement.

2.An agent assigns rewards to different states:

- +1 for reaching the goal,
- -1 for entering an obstacle,
- 0 for intermediate steps

3.2. Experimental Results

We conducted experiments in physical and virtual environments to validate the implementation of MDP-based maze exploration. We tested the robot in a 3x4 grid-world maze and a more extensive virtual 6x8 grid-world environment. The key results are summarized below:

3.2.1. 3x4 Grid-World Environment

In the physical setup, the robot successfully navigated the 3x4 maze, which associates one obstacle(inaccessible) state and two terminal states where the episode ends (reward of +1 or -1) out of the twelve states (cells of the grid) in total, achieving the following outcomes:

- Convergence of Policy: Figure 3 shows that the MDP policy iteration algorithm converged after 11 iterations, demonstrating efficient policy computation in small environments [2].
- Optimal Navigation Path: The robot followed the computed optimal policy, avoiding obstacles and reaching the goal state. The resulting path minimized cumulative costs and maximized rewards.
- Localization Performance: Localization performance was enhanced by the vision-based localization module, which accurately identified the robot's position in most cases and facilitated smooth navigation.

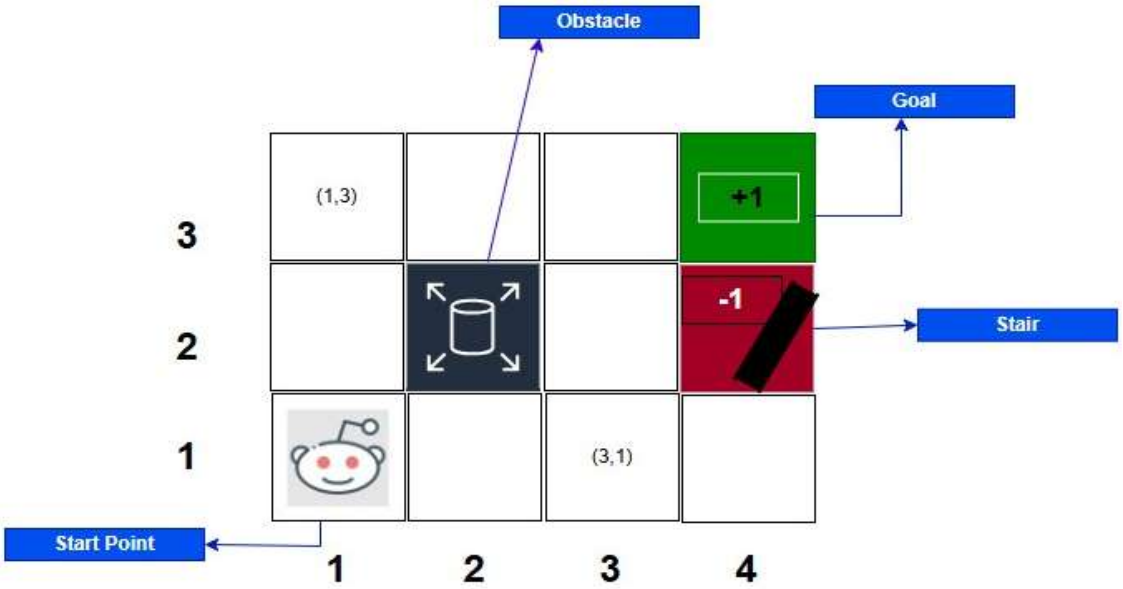

Figure 2: 3x4 Grid-World Environment with different states (Created by the authors based on [15])

3.2.2. 6x8 Grid-World Environment

To evaluate the scalability of the proposed Markov Decision Process (MDP)-based exploration strategy. We tested the system in a more enormous 6×8 virtual maze. The environment consists of 48 states, incorporating:

- There are nine obstacle (inaccessible) states, which refer to areas with obstacles (walls) where the robot cannot traverse.
- There are three terminal states, each with assigned rewards: one positive goal state and two negative penalty states.

Virtually, the robot explored the maze using MDP as its primary algorithm to decide the motion from the current cell to the next potential cell, along with the Left-hand Rule maze exploration algorithm to guide the robot during unwanted maneuvers. The Maze exploration algorithm does not affect either the optimal policy that emerged or the efficiency matrix. Overall, after a short time stamp, the optimal policy generated the as shown in Fig. 4. The final policies for both setups are included to provide a visual understanding which demonstrated the following key observations:

- Policy Convergence: The optimal policy was computed after 19 iterations, indicating increased computational demands for larger environments [4]. Since the 6×8 grid-world is 4 times larger than the 3×4 grid-world (48 states vs. 12 states), if the system scaled linearly, we would

expect 44 iterations. However, with the help of the maze exploration algorithm, the system converged into 19 iterations instead of 44. The percentage optimization is 56.82%.

- Optimal Policy Map: The computed policy effectively directed the robot to navigate the maze while avoiding prohibited cells. The policy map provided apparent direction vectors for each state. As a result, the optimal policy demonstrates the final, accepted flow that guides the robot reaching the goal state from any permissible cell in the maze.
- Efficiency Metrics: Increasing the maze size resulted in a corresponding increase in total computation time, highlighting the necessity for optimization techniques to enhance performance in larger-scale environments. A better strategy emerges from the need to achieve optimal flow convergence in a maze containing various cell types.

We included figures to illustrate the convergence plots, reward values, and final policies for both setups, helping to provide a clear visual understanding of the results.

3.3. Discussion

The results demonstrate the effectiveness of MDP-based methods for maze exploration and navigation. However, several challenges and opportunities for improvement were identified:

3.3.1. Strengths

- Policy Accuracy: The MDP algorithms generated reliable policies that guided the robot effectively, even in complex environments.
- Scalability: The approach scaled well to larger mazes, demonstrating robustness in generating optimal policies for various grid sizes.
- Flexibility: Integrating vision-based localization and sensor data enables the system to successfully facilitate real-world navigation.

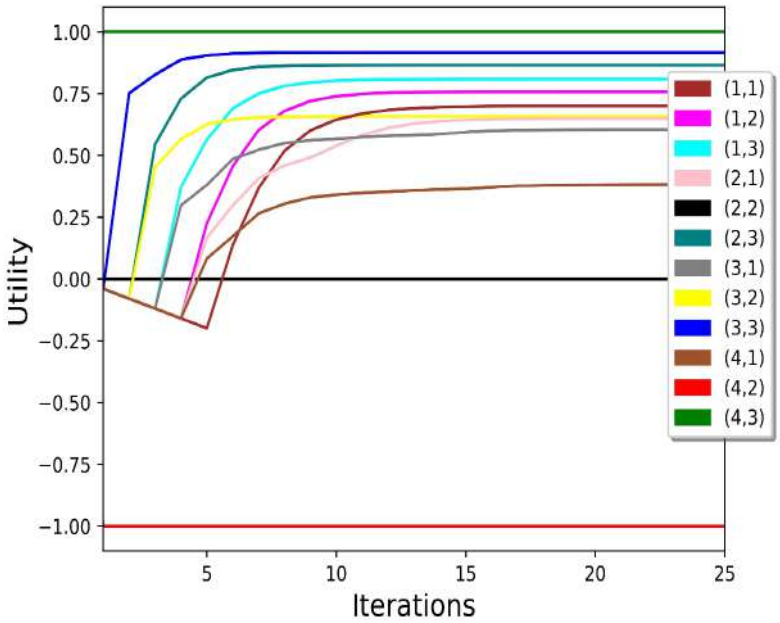

Figure 3: Convergence of the MDP policy iteration algorithm in the 3x4 grid-world environment.

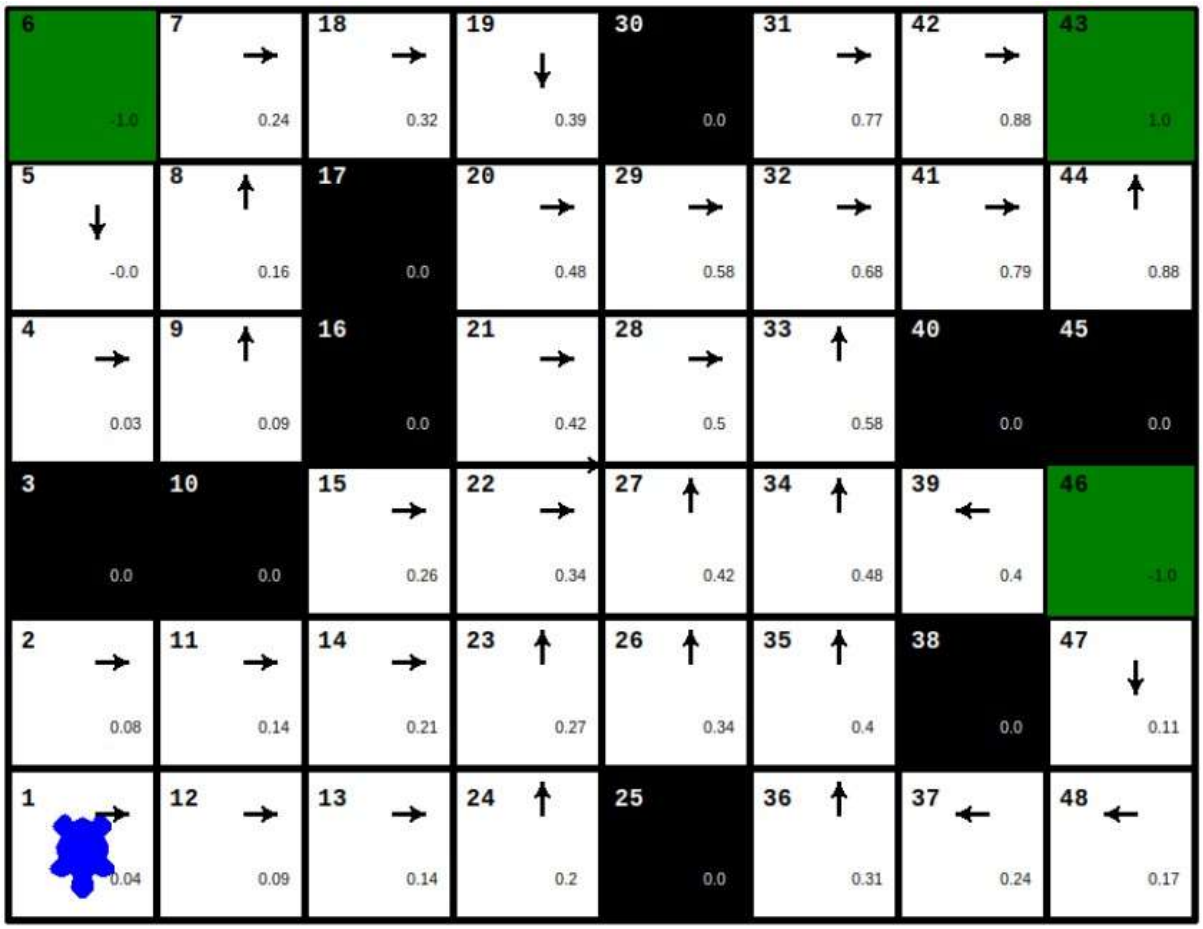

Figure 4: MDP-based Maze Exploration in a 6x8 grid-world. The figure shows the reward and policy map, where each cell represents the state of the environment. The nine black cells indicate obstacles that the robot cannot enter. The green cells represent terminal states, with rewards of -1, 1, and a final state with a +1 reward. The policy map displays optimal action for each state, guiding the robot's exploration in the maze.

4. Connecting MDPs to Predictive Control

4.1. Advantages of Predictive Control for Mobile Robots

Predictive control techniques, such as Model Predictive Control (MPC), have demonstrated significant advantages in addressing real-time adaptability and constraint handling in mobile robotics. Unlike MDPs, which focus on long-term decision-making through reward optimization, MPC excels in short-term trajectory planning by continuously predicting future states and adjusting control inputs accordingly [1,6].

Many regard MPC as one of the most effective methods for controlling autonomous systems under constraints [9]. Its ability to incorporate physical limitations (e.g., motor torque, velocity) and maintain smooth trajectories makes it a valuable complement to MDP-based approaches [2]. Its predictive nature allows the system to compute optimal control actions at each step by solving a constrained optimization problem [10]. It is particularly effective for dynamic environments where robots must respond to changes such as moving obstacles or time-varying conditions [16]. Applications of MPC in mobile robotics include:

- Obstacle avoidance in dynamic environments plays a critical role in real-time navigation [11].
- Real-time trajectory planning for autonomous vehicles is crucial for ensuring safe and efficient navigation [12].
- Coordinated control is essential for multi-robot systems to function optimally [13].

4.2. Challenges in MDP-Based Systems

While MDPs provide an optimal policy for high-level decision-making, they encounter several limitations when applied to real-world robotic systems:

- Real-Time Constraints: The iterative computation of policies in MDPs can lead to delays, especially in larger environments, limiting their applicability for fast-changing scenarios [7].
- Dynamic Environments: MDPs lack an inherent design for handling dynamic changes, such as moving obstacles or sudden environment updates [2].
- Trajectory Execution: Translating discrete state-action policies into smooth, continuous motion trajectories can be challenging without additional control layers [9].

4.3. Proposed Integration of MDPs and Predictive Control

Integrating MDPs with predictive control offers a promising approach to leverage the strengths of both methods [16]. The proposed framework involves:

- MDP for High-Level Planning: Use MDPs to generate optimal policies based on long-term goals and rewards. These policies provide a high-level decision-making framework for robots [4].
- MPC for Low-Level Control: Employ MPC to execute the MDP-generated policies in real time, ensuring smooth trajectory tracking and adherence to system constraints [8].
- Feedback Loop: Integrate a feedback mechanism so MPC informs the MDP of environmental changes, enabling policy adaptation.

4.4. Potential Benefits of Integration

The integration of MDPs and MPC can address the limitations of standalone methods while enhancing overall system performance:

- Real-Time Adaptability: MPC's predictive capabilities enable rapid responses to dynamic changes, complementing MDPs' high-level planning [10].
- Trajectory Optimization: MPC ensures smooth and efficient trajectory execution, translating discrete MDP policies into actionable continuous motion [9].
- Scalability and Robustness: The combined approach allows scalable application to complex environments while maintaining robustness to uncertainties and disturbances [11].

4.5. Applications for Combined Methods

The integration of MDPs and predictive control has broad applications in mobile robotics, including:

- Autonomous Navigation: Robots navigating warehouses, hospitals, or urban environments can benefit from the combined framework for efficient and adaptive path planning.
- Multi-Robot Coordination: Predictive control can optimize interactions between robots in collaborative tasks, while MDPs ensure high-level task allocation [13].
- Dynamic Obstacle Avoidance: The feedback mechanism between MDPs and MPC can handle real-time updates to avoid moving obstacles effectively.

5. Future Work and Conclusion

The findings from this study highlight several key areas for further research and improvement. Future work should focus on addressing the current limitations of MDP-based maze exploration and predictive control integration, including the following aspects:

- Developing Hybrid MDP-MPC Systems: While MDPs provide an effective framework for high-level decision-making [1], they lack real-time adaptability. Conversely, Model Predictive Control (MPC) excels in trajectory tracking but does not inherently optimize long-term decision-making [12]. Future work should focus on designing hybrid systems that leverage MDPs for

strategic planning and MPC for real-time control, ensuring a seamless balance between computational efficiency and adaptability in dynamic environments.

- Enhancing Localization Accuracy Through Sensor Fusion: One of the primary challenges observed in this study is the reliance on vision-based localization, which is susceptible to errors under poor lighting conditions. Future research should explore multi-sensor fusion techniques, incorporating data from LiDAR, inertial measurement units (IMUs), and ultrasonic sensors to improve localization robustness. Advanced filtering techniques, such as Kalman Filters or Particle Filters, can further enhance state estimation accuracy [11]. • Optimizing Computational Efficiency for Real-Time Applications: MDP-based decision-making suffers from scalability issues when applied to large or dynamic environments. Future efforts should explore reinforcement learning approaches, such as Q-learning or Deep Q-Networks (DQNs), to approximate value functions efficiently. Additionally, parallel computing and GPU acceleration could be utilized to speed up policy computation and real-time adaptability [3].
- Application in Real-World Scenarios: Future studies should validate the proposed hybrid MDP-MPC system in real-world environments beyond simulated grid-world setups. Potential applications include warehouse automation, autonomous navigation in urban settings, and search and rescue missions, where adaptive decision-making and precise control are crucial [13].
- Improving Obstacle Avoidance Strategies: The current MDP framework assumes a static environment. However, real-world navigation often involves dynamic obstacles. Future research should focus on integrating dynamic obstacle avoidance mechanisms using predictive models and real-time environmental perception [11].

6. Conclusion

This study explored the integration of Markov Decision Processes (MDPs) with predictive control techniques for mobile robot trajectory tracking and maze exploration. Through a case study, we demonstrated that while MDPs provide an effective framework for navigation in structured environments [4], they face limitations in real-time adaptability. To address these challenges, we examined how Model Predictive Control (MPC) can enhance trajectory tracking performance by dynamically adjusting control actions in response to environmental changes [12].

Our findings suggest that combining MDPs with predictive control can significantly improve the efficiency and adaptability of autonomous navigation systems. By leveraging the strengths of both methods, robots can achieve optimal decision-making while maintaining real-time responsiveness. The proposed approach has potential applications in autonomous robotics, warehouse automation, and dynamic path planning for mobile robots operating in uncertain environments [13].

Future research should focus on enhancing localization accuracy, optimizing computational efficiency, and applying the hybrid MDP-MPC framework in real world robotic systems. The integration of reinforcement learning techniques [2] and sensor fusion strategies [11] could further improve performance, making mobile robots more capable of handling complex, real-world navigation tasks.

In conclusion, this work revisited MDP-based maze exploration and highlighted its potential when combined with predictive control for mobile robot trajectory tracking.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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AI Models for Automatic Objects Classification in Satellite Images

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Abstract

This study investigates the application of artificial intelligence techniques for object segmentation in high-resolution satellite imagery, with a focus on the automatic classification of land cover types such as rivers, forests, and buildings. It includes a comparative analysis of traditional image processing methods and modern deep learning architectures — specifically convolutional neural networks (U-Net, DeepLabV3+, Mask R-CNN) and transformer-based models. The study outlines practical considerations for model deployment and highlights future directions, including the use of self-supervised learning, lightweight models for edge devices, and multi-modal data integration. The findings highlight the advantages of AI-driven segmentation over traditional methods, improving precision and scalability for applications in environmental monitoring, urban planning, and disaster management.

Keywords

Satellite image segmentation, artificial intelligence, deep learning, convolutional neural networks, transformers, remote sensing, land cover classification, semantic segmentation, total variation regularization, loss functions, Swin Transformer, U-Net, DeepLabV3+, Mask R-CNN, environmental monitoring, urban planning, disaster management, geospatial analysis, image processing, self-supervised learning.

1. Introduction

Satellite imagery plays a critical role in numerous domains, ranging from environmental monitoring and urban planning to disaster management and agricultural analysis. These images provide a comprehensive and up-to-date overview of the Earth's surface, enabling researchers, policymakers, and industry experts to make informed decisions. The advent of high-resolution satellite imaging has revolutionized the ability to observe, analyze, and respond to changes in the environment. For instance, satellite images can be used to track deforestation, monitor water levels in rivers, or assess the impact of urbanization. One of the key challenges in leveraging satellite imagery is the vast amount of data generated daily, making manual analysis infeasible. It necessitates the development of automated systems that can efficiently process, analyze, and extract meaningful information from satellite images. Among these tasks, object segmentation stands out as a fundamental step that underpins various applications.

Object segmentation refers to the process of identifying and delineating objects within an image, such as rivers, forests, or buildings. In the context of satellite imagery, segmentation allows for the classification and spatial mapping of different land cover types, which is essential for numerous practical applications:

- Environmental Monitoring is the process of identifying deforestation patterns, monitoring water bodies, and assessing changes in vegetation over time;
- Urban Development is the process of mapping urban growth, analyzing infrastructure distribution, and planning new developments;
- Disaster Response is the act of rapidly assessing affected areas during floods, earthquakes, or wildfires to guide relief efforts.

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Manual segmentation is not only time-consuming but also prone to errors due to the complexity of satellite images, which often include overlapping features, varying lighting conditions, and differences in resolution. It underscores the importance of employing advanced technologies, particularly Artificial Intelligence (AI), to achieve accurate and efficient segmentation.

In recent years, the integration of AI, particularly deep learning techniques, has significantly advanced the field of image segmentation. Traditional image processing methods relied on handcrafted features and domain-specific algorithms, which were limited in their ability to generalize across diverse datasets. AI-based methods, on the other hand, utilize neural networks that can learn complex patterns from large datasets. Notable advancements include:

- Convolutional Neural Networks (CNNs) are widely used for feature extraction and classification in images. Architectures like U-Net and Mask R-CNN have been specifically designed for image segmentation tasks.
- Semantic segmentation is assigning a class label to each pixel in the image, enabling detailed object identification.
- Instance segmentation is distinguishing between different objects of the same class, such as multiple buildings in a cityscape.

AI-driven segmentation not only enhances accuracy but also drastically reduces the time required for analysis. It has made it feasible to process large-scale satellite datasets in near real-time.

This study aims to explore the application of AI techniques for the segmentation of objects in satellite imagery. The primary objectives include developing a robust framework for the automatic classification of land cover types such as rivers, forests, and buildings, evaluating the performance of state-of-the-art segmentation models on satellite datasets, and identifying the challenges and limitations associated with AI-driven segmentation methods while proposing potential solutions.

2. Related works

Analyzing recent studies [1-3], it is evident that the field of automatic segmentation and classification of satellite images has significantly advanced in recent years. The application of deep learning and computer vision techniques has led to improved accuracy in land cover classification, urban planning, and environmental monitoring. Modern AI-driven methods enable precise recognition of objects such as rivers, forests, and buildings, supporting large-scale geospatial analysis.

In this regard, convolutional neural networks (CNNs) remain the dominant approach for image classification. The work [4] introduces a deep learning model that utilizes multiscale feature extraction to enhance segmentation accuracy in high-resolution satellite images. Similarly, [5] explores the use of fully convolutional networks (FCNs) for pixel-wise classification, demonstrating superior performance in detecting land cover changes. A study in [6] proposes an attention-based UNet model to improve feature localization and boundary detection, reducing misclassification errors in heterogeneous landscapes.

Recent research has also investigated hybrid models that integrate traditional machine learning with deep learning approaches. For example, in [7], a combination of random forest classifiers with deep CNNs is proposed to enhance feature selection and improve classification robustness. The paper [8] presents an ensemble learning approach that combines CNNs with support vector machines (SVMs) to refine urban area detection. Additionally, [9] explores self-supervised learning techniques to overcome the challenge of limited labelled datasets, demonstrating their effectiveness in land-use classification.

Another growing trend is the use of transformer-based architectures for satellite image analysis. In [10], a Vision Transformer (ViT) model is applied to large-scale remote sensing datasets, outperforming CNN-based methods in classification accuracy. Similarly, [11] introduces a hybrid Swin Transformer model that captures long-range dependencies in high-resolution imagery, improving segmentation results for complex terrain. Furthermore, [12] proposes a spatio-temporal transformer model for monitoring land cover changes over time, enabling more efficient change detection analysis.

Beyond supervised learning, researchers are exploring semi-supervised and unsupervised techniques for classification. The study [13] utilizes generative adversarial networks (GANs) to generate synthetic training samples, reducing dependency on manually labelled datasets. In [14], self-organizing maps (SOMs) are used for clustering satellite images, effectively identifying regions with similar land cover characteristics. The work [15] proposes a contrastive learning framework that

leverages large unlabeled datasets to improve classification accuracy with minimal human annotation.

Several studies focus on domain adaptation and transfer learning to improve model generalization across different satellite datasets. In [16], a domain adaptation framework is introduced to fine-tune pre-trained models on diverse geospatial datasets, achieving higher accuracy in cross-region classification tasks. The research in [17] explores few-shot learning techniques to classify rare land cover types with limited training samples. Meanwhile, [18] presents a meta-learning approach that adapts AI models to new satellite images with minimal re-training, significantly reducing computational costs.

Additionally, cloud computing and edge AI are being leveraged to accelerate the processing of satellite images in real-time. In [19], a cloud-based deep learning framework is developed for large-scale geospatial analysis, allowing efficient processing of massive satellite datasets. The study [20] investigates the use of edge AI devices for real-time segmentation, enabling fast decision-making in environmental monitoring applications.

2.1. Traditional Approaches to Object Segmentation in Satellite Imagery

Before the advent of AI and deep learning, object segmentation in satellite imagery relied primarily on conventional image processing and computer vision techniques. These methods often utilized handcrafted features, statistical models, and rule-based systems to identify and classify objects. One of the earliest and most commonly used approaches was thresholding, where pixel values were categorized based on predefined intensity levels. This method [21] proved to be particularly effective for binary segmentation tasks, such as differentiating water bodies from land. However, it was not capable of handling complex landscapes with multiple land cover types.

Another widely adopted technique was edge detection [22], which involved detecting boundaries between objects using operators such as Sobel, Canny, and Laplacian filters. While effective in delineating distinct objects, edge detection often struggled in cases where boundaries were unclear due to noise, shadows, or similar textures.

Region-based segmentation methods [23], such as Watershed and Mean-Shift, sought to improve edge detection by clustering pixels based on similarities in colour, texture, or spatial proximity. These methods worked well for specific applications but required extensive tuning and often failed when dealing with highly heterogeneous satellite images.

A more advanced approach was object-based image analysis (OBIA), which segmented images into meaningful objects rather than individual pixels. OBIA utilized techniques such as hierarchical clustering and region-growing algorithms, making it more effective for land-use classification. However, it still required human intervention for parameter selection and lacked adaptability to varying datasets.

Despite their utility, traditional segmentation methods had several limitations, including:

- Poor generalization across different geographic regions and image conditions;
- High sensitivity to noise and lighting variations, leading to inconsistent results;
- There is a lack of contextual understanding, as these methods relied solely on pixel values rather than learning from large datasets.

2.2. The Emergence of Machine Learning for Image Segmentation

To address the limitations of traditional methods [24], machine learning (ML) techniques were introduced, leveraging statistical models to improve segmentation accuracy. Supervised learning approaches, such as decision trees, support vector machines (SVM), and random forests, became popular for classifying satellite images. These models were trained on labelled datasets, enabling them to recognize patterns more effectively than rule-based systems.

One of the significant breakthroughs in ML-based segmentation was the adoption of k-means clustering and Gaussian mixture models (GMMs) for unsupervised classification. These methods grouped pixels based on statistical similarities, allowing for automatic identification of land cover categories. However, they still required feature engineering and struggled with complex object boundaries. A key advancement came with the introduction of deep learning [25], which eliminated the need for manual feature extraction by allowing models to learn hierarchical representations

directly from data. It marked a paradigm shift in satellite image segmentation, as deep learning models significantly outperformed traditional machine learning methods.

2.3. Deep Learning for Satellite Image Segmentation

Deep learning, particularly convolutional neural networks (CNNs), revolutionized the field of image analysis by enabling end-to-end learning of spatial features. Several architectures [26] have been developed to tackle the specific challenges of satellite image segmentation:

- Fully Convolutional Networks (FCNs) are one of the first deep-learning approaches for segmentation. FCNs replaced traditional fully connected layers with convolutional layers, allowing for pixel-wise classification.
- U-Net is an architecture designed specifically for biomedical and remote sensing applications, featuring an encoder-decoder structure that enhances segmentation accuracy.
- Mask R-CNN is an extension of Faster R-CNN that enables instance segmentation by distinguishing between different objects of the same category.
- DeepLabV3+ is a model that utilizes atrous spatial pyramid pooling to capture multiscale information, making it practical for segmenting objects of varying sizes.

These models have significantly improved segmentation accuracy in satellite imagery by learning complex spatial relationships and handling diverse environments. However, they also introduce new challenges, such as high computational costs and the need for large labelled datasets.

2.4. Comparison of Traditional and AI-Based Methods

A comparison of traditional and AI-based segmentation methods highlights the advantages of deep learning in terms of accuracy, adaptability, and scalability. The list is shown in Table 1.

Table 1
Comparison of traditional and AI-based methods

Method	Strengths	Weaknesses
Thresholding	Simple and computationally efficient	Limited to binary segmentation, sensitive to noise
Edge Detection	Effective for boundary delineation	Struggles with complex landscapes and occlusions
Region-Based Methods	Captures spatial relationships	Requires fine-tuned parameters, not scalable
Machine Learning (SVM, Random Forests)	More robust than traditional methods	Requires handcrafted features, limited contextual understanding
Deep Learning (CNNs, U-Net, Mask R-CNN)	High accuracy, automatic feature extraction	Requires large datasets, computationally expensive

2.5. Gaps in Existing Research and Future Directions

Despite significant progress in AI-driven segmentation, several challenges remain. One of the main issues is data scarcity, as high-quality labelled satellite datasets are often limited, making it difficult to scale supervised learning approaches. Another challenge lies in computational constraints, since training deep learning models requires substantial resources that may not be accessible in all research settings. Additionally, there is the problem of generalization across regions — models trained on specific geographic areas often struggle to perform accurately in different environments due to variations in landscape features.

To address these challenges, future research should focus on developing self-supervised and semi-supervised learning approaches that reduce dependence on labelled data. There is also a growing need to optimize lightweight AI models capable of real-time processing on edge devices and satellites. Furthermore, integrating multi-modal data sources, such as LiDAR and hyperspectral imagery, can significantly enhance segmentation accuracy and model robustness.

3. Methodology

3.1. Overview of the Methodology

The proposed study [27] employs AI techniques to perform object segmentation on satellite images, focusing on classifying land cover types such as rivers, forests, and buildings. The methodology consists of several key stages, including data collection, preprocessing, model selection, training, and evaluation. This structured approach ensures the development of an efficient and accurate segmentation system tailored for satellite imagery analysis. The workflow begins with the identification of suitable high-resolution satellite imagery datasets for training and evaluation. This is followed by preprocessing steps aimed at enhancing image quality, normalizing data, and preparing segmentation masks. Next, appropriate deep learning architectures optimized for segmentation tasks are selected. The training and optimization phase involves using annotated datasets and fine-tuning model hyperparameters. Model performance is then assessed using standard segmentation metrics to ensure effectiveness. Finally, deployment considerations are addressed, focusing on the real-world applicability of the system and its computational requirements. Each of these stages plays a critical role in ensuring the accuracy and robustness of the segmentation model.

3.2. Dataset Selection

Selecting an appropriate dataset is essential for training an AI-based segmentation model. This study considers publicly available satellite datasets that provide high-resolution images and corresponding segmentation masks. Some of the most commonly used datasets include:

- Sentinel-2 Dataset is a multispectral satellite dataset provided by the European Space Agency (ESA), which is widely used for land cover classification;
- LandCover.ai is a dataset specifically designed for semantic segmentation of aerial and satellite imagery featuring manually annotated masks;
- DeepGlobe Land Cover Classification Dataset is a benchmark dataset that provides annotated satellite images covering urban, agricultural, and forested areas;
- SpaceNet is a dataset containing high-resolution satellite imagery and building footprint annotations that is functional for urban planning applications.

3.3. Data Preprocessing

Before training deep learning models, raw satellite images must undergo preprocessing to enhance their quality and suitability for analysis [28]. This preprocessing pipeline involves several essential steps. First, image resizing is performed to standardize image dimensions and ensure consistency across the dataset. Next, normalization scales pixel values to a uniform range, such as [0,1] or [-1,1] — which helps facilitate stable and efficient neural network training. To improve model generalization and reduce overfitting, data augmentation techniques such as rotation, flipping, and brightness adjustments are applied to increase dataset diversity. Finally, mask generation is carried out to create binary or multiclass segmentation masks that correspond to different land cover types, providing the necessary ground truth for supervised learning.

3.4. Model Selection and Implementation

This study explores several state-of-the-art deep learning architectures for semantic segmentation, focusing on convolutional neural networks (CNNs) and transformer-based models. The selected models include:

- U-Net is a widely used segmentation model with an encoder-decoder architecture designed for biomedical and remote sensing applications;
- DeepLabV3+ is a model incorporating atrous spatial pyramid pooling, enabling multiscale feature extraction for improved segmentation accuracy;
- Mask R-CNN is a region-based convolutional neural network capable of performing both instance segmentation and object detection;

- Swin Transformer is a transformer-based model that leverages self-attention mechanisms for efficient image segmentation.

Each model is implemented using the TensorFlow and PyTorch deep learning frameworks, leveraging pre-trained weights to accelerate training and improve performance.

3.5. Training and Optimization

The training process involves feeding annotated satellite images into the selected models and optimizing their parameters using backpropagation. A key aspect of this procedure is selecting an appropriate loss function, such as cross-entropy loss for multi-class segmentation or Dice loss for imbalanced datasets. Optimization is performed using adaptive techniques, such as Adam or SGD with momentum, to adjust model parameters effectively. Learning rate scheduling is employed to dynamically adjust the learning rate during training, improving convergence. Additionally, hyperparameters like batch size and epochs are tuned to balance training efficiency with model performance. To prevent overfitting, regularization techniques such as dropout and batch normalization are also applied throughout the training process.

3.6. Model Evaluation

To evaluate the performance of segmentation models, a range of quantitative metrics is applied [29], each capturing different aspects of model accuracy. One of the most widely used metrics is Intersection over Union (IoU), which quantifies how well the predicted segmentation overlaps with the ground truth. Complementing this, the Dice Coefficient provides a measure of similarity between predicted and actual regions, making it especially effective for datasets with class imbalance. Pixel Accuracy offers a straightforward metric by calculating the proportion of correctly classified pixels in an image. In the context of instance segmentation, Mean Average Precision (mAP) is utilized to assess how accurately individual objects are detected and segmented. Collectively, these metrics enable a thorough and multi-faceted evaluation of model performance across diverse land cover categories.

3.7. Deployment Considerations

Beyond model training, practical deployment considerations are addressed, including:

- Computational Requirements is evaluating hardware demands for real-time segmentation;
- Scalability is ensuring the model can process large-scale satellite datasets efficiently.
- Edge Deployment is exploring lightweight models for satellite or UAV-based applications.

3.8. Visualization of segmentation results

Semantic segmentation is used to identify land surface types from satellite images. The most basic use of the technology is to determine water body contours to provide more accurate cartographic information. Advanced algorithms are used to map roads, identify crop types, and so on.

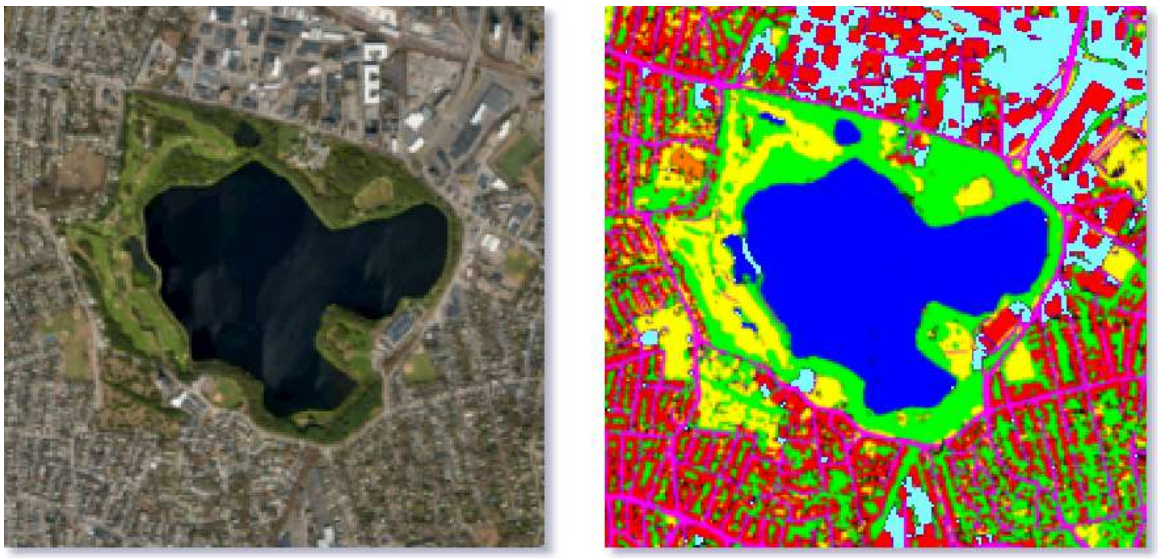

Figure 1: Semantic segmentation of satellite/aerial images [30]

The first example shows a comparison of the original satellite image and its segmented version, where different objects are marked in colours. Automatic segmentation allows you to highlight water bodies, vegetation, buildings, and roads, which is helpful for environmental monitoring and urban planning. Deep learning methods such as U-Net were used. Possible segmentation errors may be due to shadows, low resolution, or insufficient training data. This approach is practical for analyzing landscape changes and mapping territories.

Figure 2: Semantic segmentation of coastal ecosystems [31]

The second example demonstrates the process of segmentation of a satellite image for the analysis of coastal ecosystems.

This method of analysis allows for automatic classification of areas based on spectral characteristics, which is helpful for monitoring the state of water bodies, identifying environmental problems, and planning ecological protection measures.

The third figure is a good example, which combines AI with satellite data to assess real-time disaster impacts like floods, wildfires, and hurricanes. This approach enables rapid situational awareness by visually differentiating damage severity, allowing emergency response teams to prioritize critical areas.

Figure 3: An example of post-disaster images that show damaged areas with colours: green for minor damage, orange for significant damage, and red for destroyed [32]

3.9. Mathematical Formulation

To formalize the segmentation process, let I represent a high-resolution satellite image, where a feature vector x_p characterizes each pixel. The goal of segmentation is to assign a label y_p to each pixel such that the function $f: x_p \rightarrow y_p$ maps input features to semantic categories (e.g., water, vegetation, urban areas).

A typical deep learning-based segmentation model optimizes a loss function $\mathscr{L}$ to minimize the difference between predicted and ground truth labels. One commonly used function is the cross-entropy loss, defined as:

$$\mathscr{L}_{ce} = -\sum_{P}\sum_{c} y_p^c lg\left(\hat{y}_p^c\right),$$

where y_p^c is the ground truth probability for class Sat pixel e, and $\hat{y}_p^c$ is the predicted probability.

For imbalanced datasets, Dice loss is often used to improve segmentation performance:

$$\mathscr{L}_{Dice} = 1 - \frac{2\sum_{p} y_P \hat{y}_p}{\sum_{P} y_p + \sum_{p} \hat{y}_p},$$

where y_p and $\hat{y}_p$ are the ground truth and predicted segmentation masks.

To enhance the spatial coherence of segmentation predictions, a Total Variation (TV) regularization term can be introduced. This regularizer is particularly effective in reducing noise and producing smoother segmentations by discouraging abrupt changes in neighboring pixel classifications. The TV regularization term is defined as follows:

$$\mathscr{L}_{tv} = \sum_p \left(|\hat{y}_{p+1} - \hat{y}_p| + |\hat{y}_{p-1} - \hat{y}_p|\right),$$

where $\hat{y}_p$ represents the predicted probability or class value at pixel ppp. The expression quantifies the total amount of variation across neighboring pixels, effectively penalizing high-frequency fluctuations in predictions that are not supported by image features. This promotes local smoothness and improves spatial consistency in the segmented output.

However, regularization alone is not sufficient. In practice, the training of segmentation models involves optimizing a composite loss function that balances multiple objectives. For semantic segmentation tasks, commonly used components include the categorical cross-entropy loss $\mathscr{L}_{ce}$, which measures the pixel-wise classification error, the Dice loss $\mathscr{L}_{Dice}$, which is particularly useful in handling class imbalance, and the aforementioned total variation loss $\mathscr{L}_{tv}$.

The final objective function used to train the segmentation network is a weighted combination of these three terms:

$$\mathscr{L}_{total} = \alpha \mathscr{L}_{ce} + \beta \mathscr{L}_{Dice} + \gamma \mathscr{L}_{tv},$$

where α, β, γ are hyperparameters controlling the influence of each term. Tuning these coefficients is crucial for achieving optimal performance, as they determine the trade-off between segmentation accuracy, boundary precision, and spatial smoothness.

In most implementations, the choice of these weights depends on the characteristics of the dataset. For instance, datasets with noisy annotations or frequent texture artifacts may benefit from higher γ values to enforce smoother transitions.

4. Experiments and Results

To ensure reliable and reproducible results, the experimental setup is carefully designed, incorporating high-performance computing resources and standardized deep learning frameworks. The key components of the environment include:

Table 2
Computing resources

N	Computing resources	Components	Explanation
1	Hardware Configuration	GPU	NVIDIA RTX 3080 (10GB VRAM) for accelerated model training
		CPU	AMD Ryzen 9 7950X for efficient data preprocessing
		RAM	64GB to handle large satellite image datasets
		Storage	1TB SSD for fast data access and model checkpoints
2	Software and Frameworks	Python 3.8	
		TensorFlow 2.x and PyTorch 1.x	
		OpenCV for image processing	
		GDAL (Geospatial Data Abstraction Library) for handling satellite image formats	
		Albumentations for data augmentation	
3	Dataset Specifications	Image resolution	512 × 512 and 1024 × 1024 pixels
		Number of classes	3 (rivers, forests, buildings)
		Training-validation-test split	70%-20%-10%

By using this experimental environment, we ensure that the results are optimized for both accuracy and computational efficiency.

The training process involves fine-tuning hyperparameters to achieve optimal segmentation accuracy. Several aspects of the training procedure are adjusted:

- Experimented with 8, 16, and 32 to balance GPU memory usage and convergence speed;
- Initialized at 0.001 with a step decay to 0.0001 using ReduceLROnPlateau;
- Optimizers Adam and SGD were tested, with Adam providing better stability in the early training phases;
- Set to 100 number of epochs, with early stopping applied when validation loss plateaued;
- Loss Functions are Dice Loss for imbalanced datasets (improves segmentation for small objects like rivers) and Categorical Cross-Entropy for multiclass segmentation.

These hyperparameters were determined through an extensive grid search, ensuring that the models achieved the best possible performance. The trained models were evaluated using standard

segmentation metrics, and the results were compared across different architectures. The performance of each model is summarized in Table 3.

Table 3
The performance of models

Model	IoU (Intersection over Union)	Dice Coefficient	Pixel Accuracy	Training Time (per epoch)
U-Net	85.2%	89.4%	92.3%	12 min
DeepLabV3+	83.7%	88.2%	93.1%	15 min
Mask R-CNN	81.5%	86.8%	91.5%	18 min
Swin Transformer	86.8%	90.1%	92.8%	22 min

From these results, we observe that U-Net performs well across all metrics, making it a strong choice for semantic segmentation tasks. Its encoder-decoder architecture with skip connections allows it to preserve spatial information, which is essential for delineating land cover boundaries accurately.

DeepLabV3+ achieves the highest pixel accuracy, which is particularly beneficial for large-area segmentation tasks where overall classification consistency is critical. Its use of atrous convolution and multi-scale context aggregation contributes to its strength in handling spatially diverse features.

Mask R-CNN provides instance-level segmentation, which is valuable for distinguishing between multiple occurrences of the same object class, such as separate buildings or vehicles. However, it shows a slightly lower IoU due to challenges in dealing with complex and noisy background textures commonly found in natural landscapes. This indicates a trade-off between instance-level precision and overall semantic coherence.

Swin Transformer achieves the best overall performance across metrics, benefiting from its hierarchical vision transformer design and self-attention mechanisms that effectively model long-range spatial dependencies. This makes it especially powerful for capturing subtle patterns and context in high-resolution satellite images. However, this superior accuracy comes at a higher computational cost, which may limit its practical deployment in resource-constrained environments, such as real-time onboard satellite processing or edge devices.

Despite promising results, several challenges remain:

- Misclassification in boundary regions (small objects such as narrow rivers are sometimes misidentified as roads);
- Variability in lighting and atmospheric conditions (shadows and haze in satellite images introduce noise);
- Data scarcity for specific regions (the model generalizes well for well-represented landscapes but struggles with less common environments).

5. Discussions

The experimental results demonstrate the effectiveness of deep learning models for satellite image segmentation, revealing notable variations in performance across different architectures. High Intersection over Union (IoU) and Dice coefficient scores confirm that the models can accurately differentiate between various land cover types, such as rivers, forests, and buildings. Among the evaluated models, the Swin Transformer consistently outperformed traditional CNN-based architectures, benefiting from self-attention mechanisms that effectively capture complex spatial relationships in satellite imagery. U-Net, despite its relatively simple design, delivered competitive results and remains a practical choice for large-scale segmentation tasks due to its computational efficiency and ease of training. DeepLabV3+ excelled in capturing fine details, which is especially advantageous for segmenting narrow rivers and small structures. In contrast, Mask R-CNN proved useful for instance segmentation but encountered difficulties with semantic segmentation of natural landscapes, primarily due to the complexity and variability of background textures.

Several key observations emerged from the analysis. Boundary regions between different land types presented consistent challenges, often resulting in misclassifications at the edges. Data imbalance also impacted model performance, as areas with fewer training examples — such as sparsely represented forest zones, tended to be segmented less accurately. Moreover, model

generalization was found to depend heavily on dataset diversity; models trained on geographically limited data often struggled to accurately segment landscapes from unfamiliar regions. These findings highlight both the strengths and current limitations of AI-based segmentation methods when applied to real-world satellite imagery.

Traditional satellite image segmentation methods, such as thresholding, edge detection, and classical machine learning techniques (e.g., Random Forests, SVM), have been widely used in remote sensing applications. However, these methods often struggle with complex, high-resolution images due to their limited ability to capture hierarchical spatial relationships. They typically rely on handcrafted features and shallow representations, which makes them less effective in handling variations in texture, lighting, and object scale. As a result, their performance tends to degrade in heterogeneous landscapes or when applied to large and diverse satellite datasets.

The list of advantages and disadvantages of models is shown in Table 4.

Table 4
Advantages and disadvantages of models

Method	Advantages	Disadvantages
Thresholding & Edge Detection	Simple, fast, interpretable	Sensitive to lighting conditions and noise
Random Forests & SVM	Effective for small datasets, interpretable	Requires handcrafted features, limited scalability
CNN-based Models (U-Net, DeepLabV3+)	High accuracy, learns spatial hierarchies	Computationally expensive
Transformer-based Models (Swin Transformer)	Captures long-range dependencies, state-of-the-art performance	Requires large datasets and computational power

The results show that deep learning methods significantly outperform classical approaches in terms of segmentation accuracy and robustness. Transformer-based architectures, in particular, demonstrate superior capability in handling complex satellite imagery, suggesting a shift towards these models in remote sensing applications.

The automatic classification of land cover using satellite imagery has numerous real-world applications across various domains. In environmental monitoring [33], AI-based segmentation enables the detection of changes in river paths due to climate change or deforestation, allowing researchers to track the degradation of natural landscapes over time. It also facilitates the assessment of flood-prone areas, contributing to disaster prevention strategies. Similarly, the ability to analyze forest cover loss and land degradation helps environmental organizations and policymakers take appropriate conservation measures.

Urban planning and infrastructure development [34] also greatly benefit from automated segmentation methods. By analyzing satellite images, city planners can monitor urban expansion, identify informal settlements, and evaluate changes in land use. This data is essential for designing sustainable cities and ensuring efficient infrastructure growth. Automated segmentation allows authorities to track the development of new buildings and road networks, supporting informed decision-making in large-scale construction projects.

Despite the advancements in AI-based satellite image segmentation, several challenges remain that hinder widespread adoption and practical implementation. One of the primary issues [35] is the generalization of models across different geographic regions. Satellite images vary significantly based on atmospheric conditions, vegetation types, and urban structures, making it difficult for a model trained on one dataset to perform well in other locations. This limitation necessitates domain adaptation techniques or the collection of diverse training data to improve robustness [36-37]. Another significant challenge [38] is the issue of class imbalance and rare object detection. In many satellite datasets, certain land cover types, such as rivers or buildings, are underrepresented compared to dominant classes like forests or open land. This imbalance leads to biased model predictions, where rare classes are often misclassified or ignored. Addressing this problem requires specialized techniques such as data augmentation, focal loss, and synthetic data generation to ensure balanced learning [39].

6. Conclusions

This study assessed the application of artificial intelligence techniques for object segmentation in satellite imagery, with a specific focus on the automatic classification of land cover types such as rivers, forests, and buildings. A comprehensive comparison was conducted between traditional image processing methods and modern deep learning architectures, including convolutional neural networks (U-Net, DeepLabV3+, Mask R-CNN) and transformer-based models (Swin Transformer).

Experimental results demonstrated that deep learning methods significantly outperform traditional approaches in terms of segmentation accuracy, boundary delineation, and generalization across diverse landscapes. Among the tested models, the Swin Transformer achieved the highest accuracy metrics, while U-Net remained a computationally efficient and competitive baseline. However, the performance gains of advanced models come with higher computational costs and increased demand for annotated data.

Despite outcomes, the study identified key limitations in current AI-based segmentation approaches. These include: reduced model performance in regions with limited training representation, difficulty in accurately classifying boundary zones and rare object classes, and challenges in generalizing to unseen geographic areas. The research also highlighted the importance of selecting appropriate models based on deployment scenarios — particularly when balancing performance with computational efficiency.

In conclusion, the findings underscore the practical potential of deep learning in satellite image segmentation and emphasize the necessity of addressing current challenges to facilitate broader adoption in environmental monitoring, urban development, and disaster response scenarios.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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An Increased Robust Speech Enhancement of Superdirective Beamformer

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Abstract

Microphone array (MA) technology commonly implemented in almost all acoustic equipments, such as, hearing aid, surveillance devices, smart phone, cochlear implant, voice - controlled device, teleconferencing system for extracting the desired target speaker while suppressing background noise, annoying recording scenario without speech distortion. MA beamformer use the priori spatial information about the designed distribution of MA, the characteristics of environment and the ability of combination with single-channel approach to obtain a steerable beampattern in a specified direction of sound source for recovering the clean speech data from the noisy mixture with high directivity index and high satisfactory speech quality. A superdirective (SDB) beamformer is one of the most helpful beamforming methods for preserving the original speech component in the diffuse noise field. SDB beamformer applied to numerous speech applications because of its advantages and easy implementation. Under realistic recording scenario, due to the complex environment, the inaccurate estimation of preferred direction of arrival (DoA) of useful signal, the error of sampling rate, the different speech sensitivity, the overall SDB beamformer's performance often corrupted. The speech distortion, musical noise, the remained noisy component usually exists and degrades the speech quality of the final output signal. In this contribution, the author proposed method for increasing robust speech enhancement of SDB beamformer in adverse environments. The numerical simulation has confirmed the effectiveness of the author's suggested technique in improving the speech quality by removing musical noise, background noise at SDB beamformer's output signal.

Keywords

Microphone array, speech enhancement, speech quality, noise reduction, beamforming.

1. Introduction

Nowadays, the using of MA technology has been popular and significantly increases the overall speech enhancement of various types of speech applications. MA use the spatial information about designed geometry, the preferred steering vector, the characteristic of surrounding noise, the properties of background noise, the coherence of captured MA signals to obtain high - directional beampattern towards the sound source while suppressing interference, third - party talker, as in Figure 1. MA beamforming, which owns the advantage of noise reduction and speech enhancement simultaneously, allows achieving the original speech component without distortion. Compared with single - channel approach, MA beamforming has the flexible working with different recording scenarios, such as, coherent/incoherent, diffuse and other complex situations.

MA beamforming technique can be categorized into two groups: the fixed beamformer and adaptive beamformer. The fixed beamformer bases on the prior information of incident angle of helpful signal to achiveve the beamformer's coefficient. Fixed beamformer includes Delay - and - sum (DAS) beamformer [1], which often used in almost digital signal processing system. Adaptive beamformer exploit the properties of recorded data, the rapid changed environmental factors, the constrained criteria of minimizing the total output noise power for recovering the clean speech data. Differential microphone array (DIF) [2-3], Minimum Variance Distortionless Response (MVDR) [4-6], Linearly Constrained Minimum Variance (LCMV) [7-8], Generalized sidelobe canceller (GSC) [9-10] and SDB Beamformer [11-19] is the most helpful beamforming technique, which common installed into multi-channel signal processing system to achieve the original speech data while removing total noise with high speech quality, perceptual metric listener.

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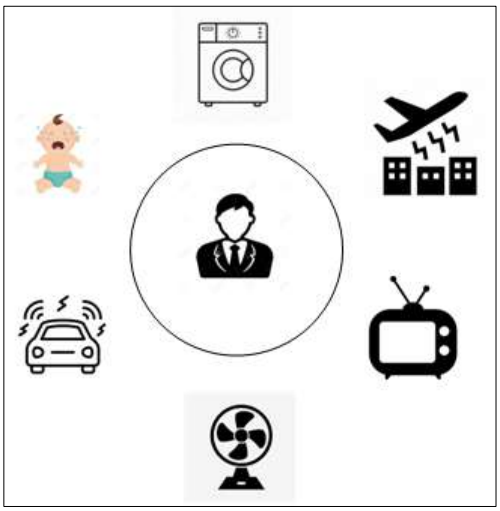

Figure 1: The complex and annoying environment around the human - life

As in Figure 2, SDB beamformer uses the properties of diffuse noise field to extract the desired talker at certain location with high directivity index. However, due to the complex and annoying environment, the error of estimation the preferred steering vector, the displacement of MA distribution, the overall SDB beamformer's performance often decreased. Consequently, speech distortion, musical noise still be challenging problem. There are numerous efforts were studied for dealing this task. The scheme of MA beamforming is given by Figure 3.

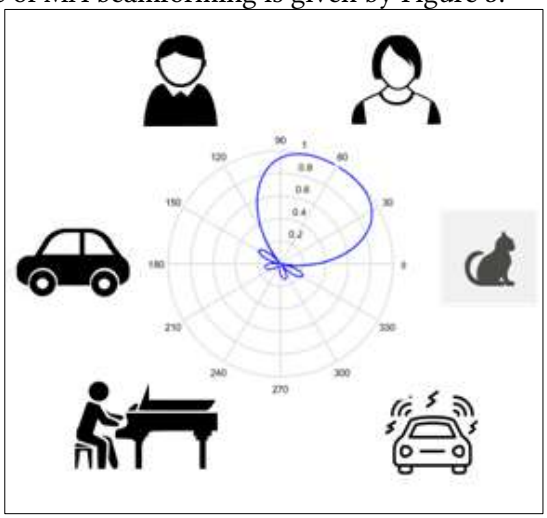

Figure 2: The complex and annoying environment around the human - life

Atkins A [11] proposed an efficient designed beamformer with trade-off between high directivity and low white noise amplification. The numerical simulations demonstrate controlled tuning of various gain properties of speech enhancement and increase the overall SDB evaluation in realistic situations.

Berkun R [12] uses a tunable regularization parameter, which addresses the problem of directivity factor (DF) and white noise gain (WNG) of SDB beamformer. The conducted experiment has confirmed the effectiveness of the author's suggested approach in adjusting DF and WNG.

In [13], the author suggested scheme combination of DAS beamformer and regularized SDB beamformer to reach high directivity factors while suppressing background noise. This direction research derives analytic closed-form expressions of the beamformer gain with controlling WNG or DF.

Wang J [14] suggested method for designing the fractional - order SDB beamformer to obtain the high maximum directivity factor in the spherical and isotropic noise field. The promising result has verified the advantage of this approach.

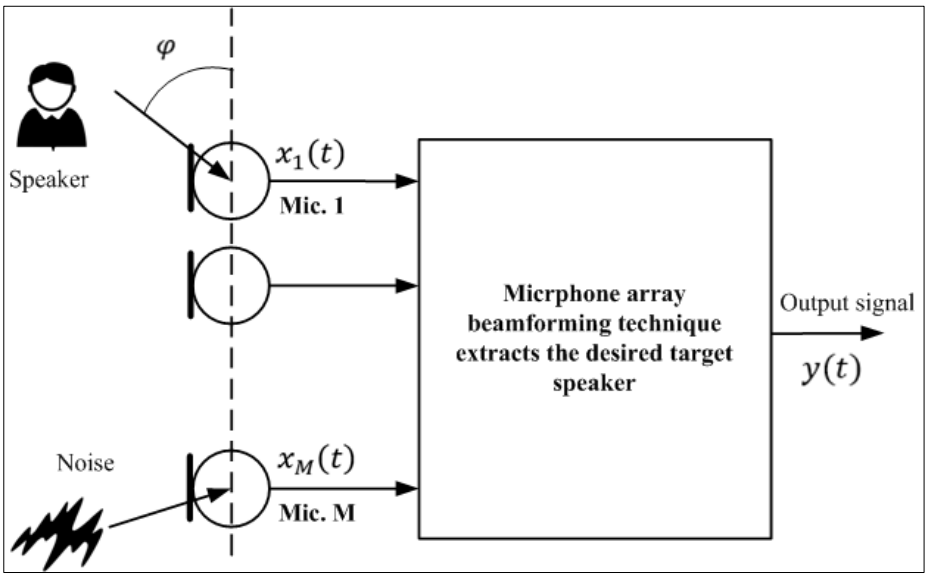

Figure 3: The principal working of microphone array beamforming

Yang X [15] addressed the problem of imperfections, such as adverse and self-noise, sensor mismatches by applying a joint optimization approach with efficient post - Filtering and robust SDB beamformer, which based on constrained WNG or utilizes diagonal loading technique. Experimental results show the improved robustness of SDB beamformer under various recording scenarios.

Gong P [16] presented an optimization of problem for designing beamformer by utilizing constrained criteria of WNG and least - squares. The author uses alternative direction penalty method (ADPM) algorithm to solve and achieve robust signal processing system of SDB beamformer.

In [17], Chen X studied the robustness of SDB beamformer and derived optimum different solutions to resolve array imperfections. The author approach utilized quadratic eigen value (QEP) to obtain the maximum possible DF and constrained WNG.

A data-driven approach, which controls WNG threshold for obtaining robustness speech enhancement, was presented [18]. The suggested method outperformed speech enhancement, noise reduction, high fidelity of the desired acoustic signal in comparison with traditional SDB beamformer.

Huang G [19] proposed diagonalization of the noise pseudo-coherence matrix of the desired/noise signals and Fourier matrix to properly select the dimension of subspace and more flexible WNG and DF than the conventional regularized SDB beamformer.

However, these above approaches performed in laboratory condition with proper environmental factors. Due to the complex and annoying recording situation, the displacement of MA geometry, the inaccurate estimation of preferred steering vector, the error of sampling frequency, the microphone mismatches, the different microphone sensitivities, SDB beamformer's evaluation usually degraded. In this paper, the author introduces modifying covariance matrix of complex diffuse noise field and enhanced steering vector to obtain more robustness of SDB beamformer. The author's method improves the real-time SDB beamformer's performance without processing large database.

2. Superdirective beamformer

In this section, the principal working of SDB beamformer will be presented. The author uses dual - microphone array (DMA2) system to describe the representation of observed MA signals in Figure 4. In the currently considered frame k, the frequency f, the received array signals $X_1(f,k), X_2(f,k)$ can be formulated in the short-time Fourier transform (STFT) as:

$$X_1(f,k) = S(f,k)e^{j\Phi_s} + N_1(f,k) \quad (1)$$

$$X_2(f,k) = S(f,k)e^{-j\Phi_s} + N_2(f,k) \quad (2)$$

Where $S(f,k)$ is the original speech component, $N_1(f,k), N_2(f,k)$ is the additive noise, $\Phi_s = \pi f \tau_0 \cos(\theta_s)$, θ_s is the preferred steering vector of the interest useful signal to axis of DMA2, $\tau_0 = d/c$, d is the distance between two mounted microphones, $c = 343(m/s)$ is sound speed propagation in the fresh air.

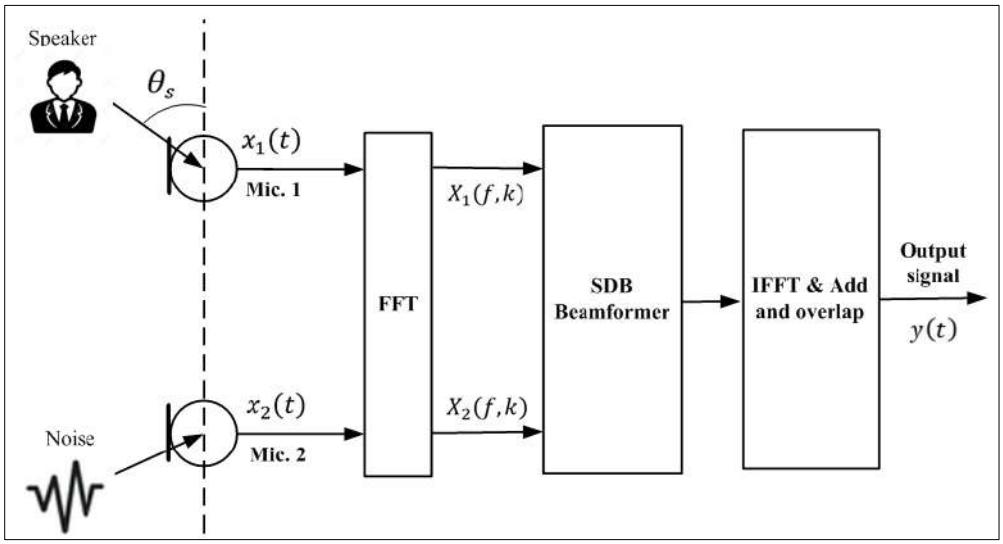

Figure 4: The scheme of SDB beamformer in the frequency - domain

If we denote $X(f,k) = \begin{bmatrix} X_1(f,k) & X_2(f,k) \end{bmatrix}^T$, $N(f,k) = \begin{bmatrix} N_1(f,k) & N_2(f,k) \end{bmatrix}^T$, $D_s(f,\theta_s) = \begin{bmatrix} e^{j\Phi_s} & e^{-j\Phi_s} \end{bmatrix}^T$, T is transpose operator, the equation (1)-(2) can be rewritten as:

$$X(f,k) = S(f,s)D_s(f,\theta_s) + N(f,k) \quad (3)$$

The essential core problem of speech enhancement is determining an optimum coefficient $W(f,k)$ for obtaining approximate clean speech data.

$$\hat{S}(f,k) = W^H(f,k)X(f,k) \quad (4)$$

where H is conjugate operator.

And $\hat{S}(f,k) \approx S(f,k)$.

In the diffuse noise field, SDB beamformer's weight can be computed as:

$$W_{SDB}(f,k) = \frac{\Gamma^{-1}(f)D_s(f,\theta_s)}{D_s^H(f,\theta_s)\Gamma^{-1}(f)D_s(f,\theta_s)} \quad (5)$$

$$\Gamma(f) = \begin{bmatrix} 1 & \frac{\sin(\omega\tau_0)}{\omega\tau_0} \\ \frac{\sin(\omega\tau_0)}{\omega\tau_0} & 1 \end{bmatrix} \quad (6)$$

Where $\omega = 2\pi f$.

SDB beamformer especially effective in diffuse noise field with high directional beampattern towards the sound source. Because of the complex and annoying environment, the displacement of MA distribution, the inaccurate estimation of incident angle of the impinging helpful signal, the microphone mismatches, the different microphone quality, the error of sampling frequency, the moving head of speaker during a conversation, the existence of non-directional noise or undetermined reason, SDB beamformer's performance often degraded. Consequently, the musical noise or speech distortion occurs and significantly effects speech quality.

For overcoming this drawback, in the next section, the author proposed an effective modified SDB beamformer for decreasing the speech distortion, musical noise, noise level and increasing the perceptual metric listener and speech intelligibility.

3. The author's proposed method

The author's ideal is enhancing the accurate estimation of steering vector $D_s(f,\theta_s)$ and modifying the covariance matrix $\Gamma(f)$, which according to the rapidly changing environmental factors.

Due to the complex environment, the steering vector can be expressed in the way:

$$D_s(f,\theta_s) = \left[e^{j\Phi_s} \quad (1-\beta) e^{-j\Phi_s} \right]^T \tag{7}$$

where β presents the distortion of clean speech data at second microphone in comparison with first microphone and $0 < \beta < 1$. In this paper, the author uses the information of standard deviation of diagonal loading of noisy covariance matrix, and $\beta = \text{std}(\text{diag}(\Psi_{NN}(f,k))$ [20], where $\Psi_{NN}(f,k) = E\left\{ N^H(f,k) N(f,k) \right\}$ is the covariance matrix of noise. β leads to 0 and β presents the error of representation of speech component at the observed microphone array signals. The noisy covariance matrix can be computed by using Voice Activity Detection (VAD) [21] for determining whether frame is the only noise.

As we know that, the coherence between two points in diffuse noise field can be formulated as $\Gamma_{X_1X_2}(f) = \dfrac{\sin(2\pi f \tau_0)}{2\pi f \tau_0}$. The author proposed using the speech presence probability $SPP(f,k)$ [22] to adjust $\Gamma_{X_1X_2}(f)$ as the following equation:

$$\Gamma_{X_1X_2}(f) = \frac{\sin(2\pi f \tau_0)}{\left(1 + (1 - SPP(f,k)) \dfrac{\sigma_n^{\,2}}{P_{nn}(f,k)}\right) 2\pi f \tau_0} e^{j2\Phi_s} \tag{8}$$

where $\sigma_n^{\,2}$ is covariance of uncorrelated noise, $P_{nn}(f,k)$ is spectral density of diffuse noise field [23].

The equation (7) contains the steering vector and ensure the robustness of the coherence between two points in diffuse noise field. Therefore, the coherence matrix can be modified as the following equation:

$$\Gamma(f) = \begin{bmatrix} 1 & \Gamma_{X_1X_2}(f) \\ \Gamma_{X_1X_2}(f) & 1 \end{bmatrix} \tag{9}$$

With the improved steering vector and modified coherence matrix in complex diffuse noise field according to the rapidly changing recording scenario, the author's proposed technique can be applied for adaptively achieving the optimum coefficient.

4. Experiments

In this section, the author aims at demonstrating the effectiveness of the suggested technique (SDB-sgt) in enhancing SDB beamformer's robustness speech enhancement with increasing the speech quality in the term of the signal - to - noise ratio, reducing musical noise and noise level at SDB beamformer's output signal. The experiment was conducted in living room with the existence of interference, non - directional noise, third - party talker, washing machine and other undetermined sources. A talker stands at distance $L = 4(m)$, the incident angle of helpful signal to the axis of dual - microphone system (DMA2) is $\theta_s = 90(\deg)$, the distance between two mounted microphones is $d = 5(cm)$. For capturing the clean speech data, these parameters were set: $nFFT = 512$, the sampling frequency $Fs = 16kHz$, overlap 50%. An objective measurement [24] was implemented for calculating the speech quality in the term of signal-to-noise (SNR) ratio. The scheme of demonstrated experiment is shown in Figure 5.

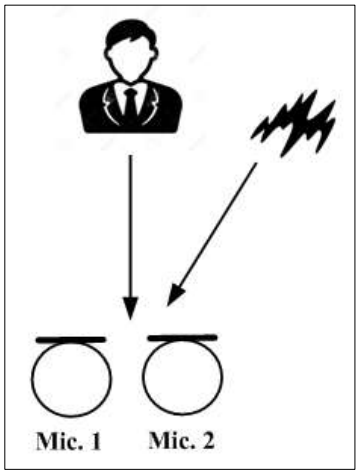

Figure 5: The conducted experiment to illustrate the advantage of the author's proposed method
The waveform of microphone array signals is given in Figure 6 and Figure 7.

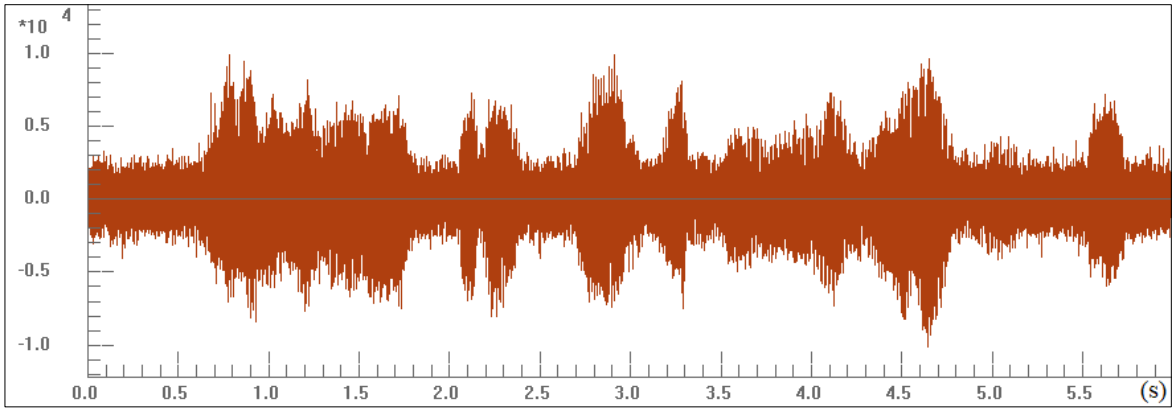

Figure 6: The waveform of received array signals

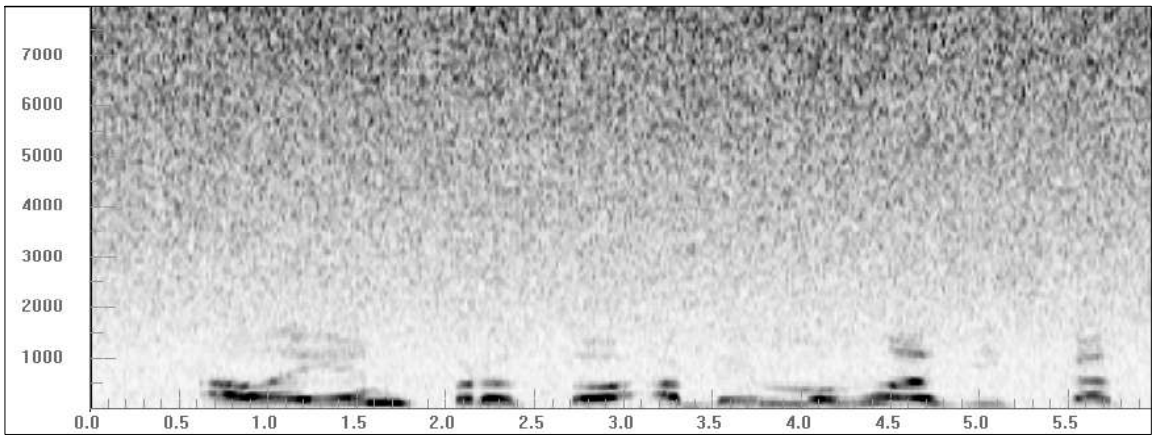

Figure 7: Spectrogram of received array signals

For further signal processing, smoothing parameter $\alpha = 0.1$ was used for implementing SDB beamformer to extract the target speaker. The obtained results are given in Figure 8 and Figure 9.

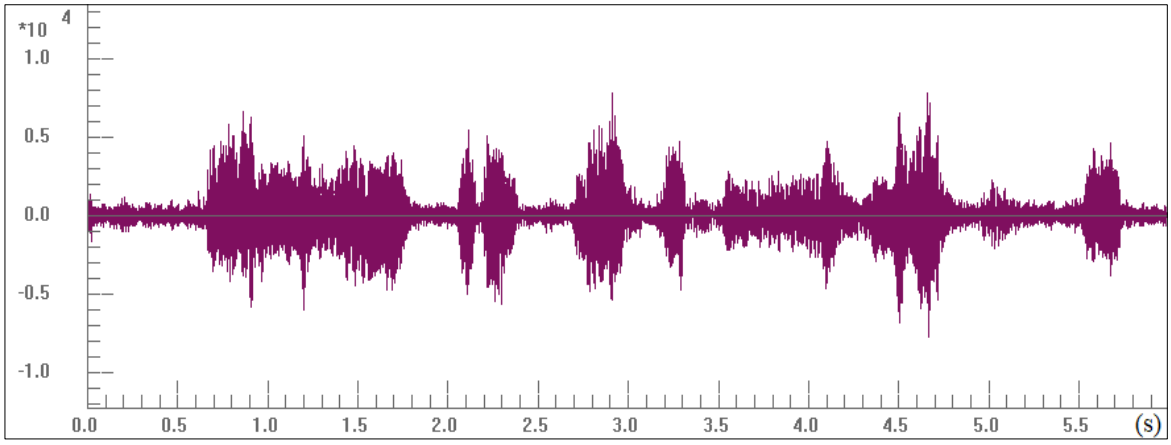

Figure 8: The processed signal by applying SDB - beamformer

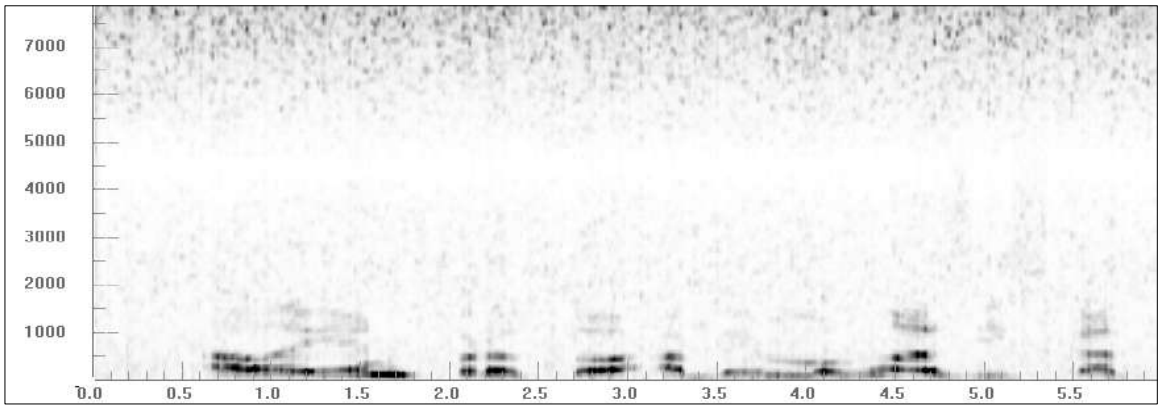

Figure 9: Spectrogram of SDB – beamformer's output signal

Because of the error of sampling rate, the different microphone sensitivities, the displacement of designed microphone distribution, the inaccurate estimation of preferred steering vector, the moving head of speaker, the adverse environment, SDB beamformer's evaluation often degraded. The existence of speech distortion, musical noise, remained noise corrupt the speech quality. Therefore, the author suggested improving the accurate calculation of steering vector and modified the noisy coherence matrix increase SDB beamformer's performance in adverse environment.

The promising result of SDB-sgt is given in Figure 10 and Figure 11. Figure 12 describes the comparison of energy between the observed microphone array signals, the processed signals by SDB-beamformer, SDB-sgt.

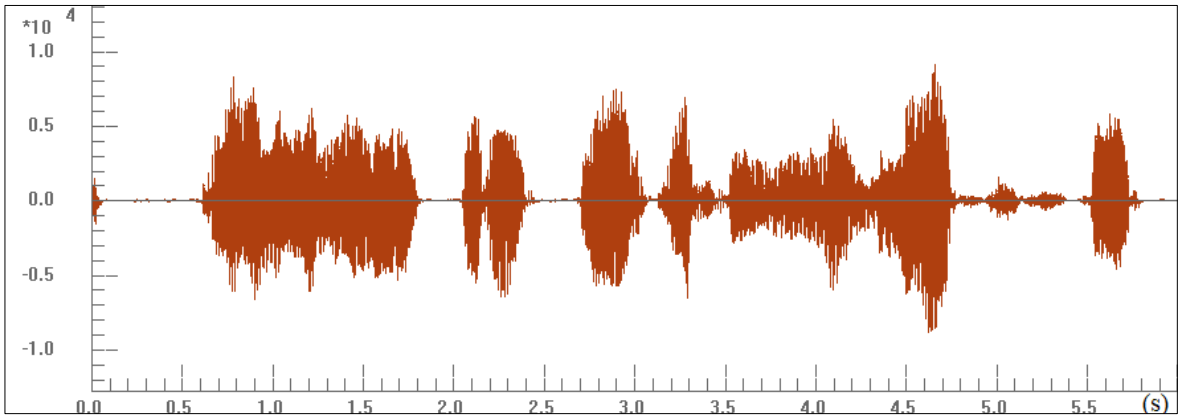

Figure 10: The processed signal by utilizing SDB-sgt

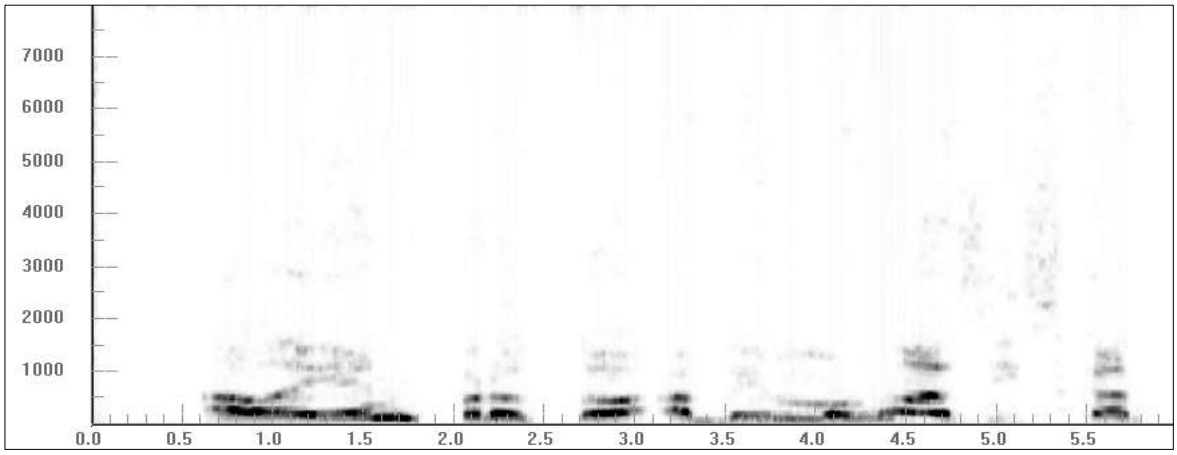

Figure 11: Spectrogram of SDB-sgt's output signal

The advantage of SDB-sgt has been confirmed with the decreasing the musical noise, noise reduction to 9.5 dB and Table 1 shows the increased the SNR from 10.9 to 12.7 dB.

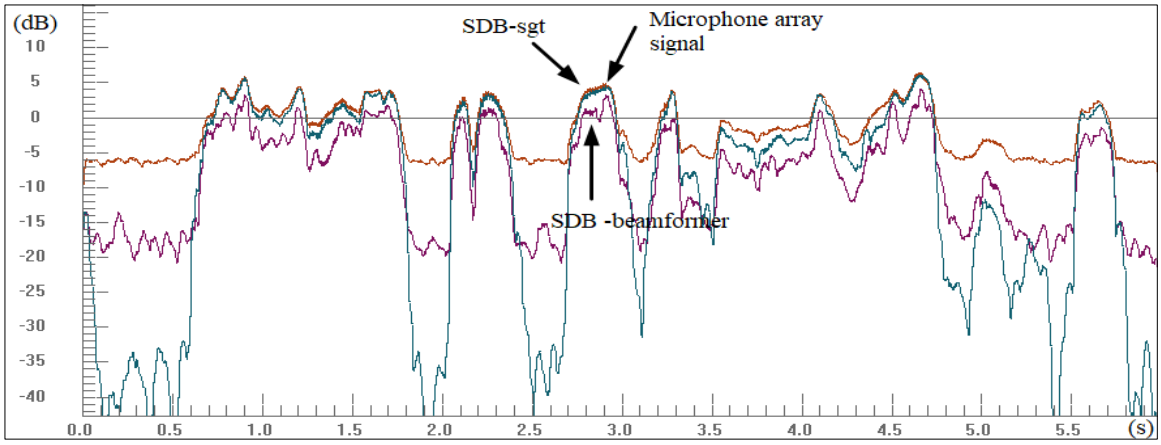

Figure 12: The comparison energy between microphone array signal and processed signals by SDB - beamformer, SDB - sgt

Table 1

The comparison speech quality (dB)

Method	Microphone	SDB-beamformer	SDB-sgt

Estimation	array		
NIST STNR	6.5	19.2	30.1
WADA SNR	3.6	12.7	25.4

The effectiveness of the author's proposed method was illustrated through the numerical simulations. The approach modifies the steering vector and the formulation of coherence between two points sources, which exploit the speech presence probability and standard covariance matrix of observed microphone array signals. The modified covariance matrix and enhanced steering vector adaptively change according to the characteristics of surrounding noise, the complex recording scenario. Therefore, the updating these necessary parameters allows improving the robustness of SDB beamformer in complex diffuse noise field. Steering vector, which contains the direction and source location, plays an important role in SDB beamformer in extracting the desired target speaker. Accurate estimation of steering vector and modified covariance matrix of complex diffuse noise allow increasing SDB beamformer's performance in realistic recording environment.

5. Conclusion

In this contribution, the author proposed an effective modified steering vector and covariance matrix of diffuse noise field in presence of annoying recording scenario. The obtained numerical results have showed the effectiveness of musical noise reduction, noise level suppression and increasing the speech quality in the term of signal-to-noise ratio from 10.9 to 12.7 dB. The author's approach based on adaptive tracking and adjusting the steering vector and covariance matrix according to the simultaneous changing environmental factors. The suggested technique incorporates the speech presence probability to enhance the robustness of computing the necessary parameter for determining SDB beamformer's coefficient. The above method can be integrated into multi-channel system for dealing other complicated problems, such as speech recognition, reverberation.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Analysis of grouping tuning parameters in flower-cutting optimization heuristics for efficient space allocation problem with item categorization

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Abstract

This study explores the concepts of computational optimization heuristics for item categorization and allocation on distribution center racks. Properly organizing products on racks in warehouses or distribution centers according to their respective categories is essential for efficient operations. The research proposes the flower-cutting optimization heuristics with 17 tuning parameters. Special attention is given to examining the effect of two grouping tuning parameters on the number of generated product allocations and their implications for space utilization, accessibility, and operational efficiency: implements a grouping strategy where, for each total width, only one product allocation with the maximum total profit is considered; adopts a grouping strategy where, for each total profit and profit ratio, only one product allocation with the minimum total width is selected. The experiment revealed that the implementation of grouping tuning parameters plays a crucial role in substantially reducing computational requirements while preserving the quality of solutions. By narrowing the solution space, these parameters ensure that the heuristics efficiently produce near-optimal allocations. This streamlined approach enhances the practicality of addressing large-scale shelf space allocation challenges, making the heuristics highly applicable to real-world scenarios.

Keywords

Space allocation, optimization heuristics, decision-making/process, item categorization

1. Introduction

Dividing the warehouse shelving into zones for different product categories or types allows for locating products much easier. In this case, for example, household goods, electronics, clothing, etc., can be stored in different areas of the racks, helping order pickers quickly find the products ordered by customers. This also guarantees effective stock management, provides easy access to products, and reduces the possibility of product damage.

We introduce novel flower-cutting optimization heuristics aimed at addressing the challenges identified in the shelf space allocation problem with specific product categorization and additional item types included in the main categories. Our approach incorporates two heuristic variants, each characterized by a unique sorting sequence for allocation prioritization. There were 17 tuning parameters implemented. However, this research mainly focuses on key grouping parameters for tuning: (1) parameter 7, which limits product allocations to one per total width, maximizing total profit. (2) parameter 9, which limits product allocations to one per total profit and profit ratio, minimizing total width. By combining innovative heuristics with parameterized selection strategies, the flower-cutting approach effectively balances complexity and practical applicability, making it a robust tool for solving shelf space allocation challenges.

Earlier research has investigated the development of heuristics for resource allocation problems, highlighting the significance of tuning parameters to optimize the solution process. These parameters are crucial for narrowing the solution space, effectively reducing complexity while maintaining solution quality [1]-[2].

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2. Literature review

Assortment planning refers to the process of selecting and managing the range of items that are available for distribution through a supply chain. In distribution centers, effective assortment planning ensures that the right items are stocked in appropriate quantities to meet customer demand while optimizing inventory levels.

For the formulation of assortment planning, the authors [3] employed an exogenous demand model and integer programming. They present a heuristic to tackle larger problems and solve a number of small problems by thorough enumeration to show how assortment and stocking decisions depend on the characteristics of predicted substitution behavior [3].

The researchers [5] introduced the practice of adjusting the store layout and changing the product allocations multiple times each day to match the changing customers' needs at different hours of the day. In this case, the customers can easily find their favorite products in the supermarket.

Online assortment planning requires a strategic approach to digital catalogue management, ensuring a diverse yet manageable range of products that align with consumer preferences and market trends. This often involves sophisticated algorithms and data analysis to continuously refine the product mix, enhancing the online shopping experience and operational efficiency.

Another researcher [6] developed a model that maximizes the revenue of impulse purchases considering the layout of grocery stores and also maximizes customer satisfaction with product allocations with regard to adjacencies of related departments.

Shelf space allocation refers to the process of assigning physical space on store shelves (or within distribution center storage areas) to different products in a way that maximizes profitability, sales, and operational efficiency. This issue becomes increasingly important in distribution centers as they prepare stock for retail stores or direct customers.

The researchers in [7] provided a revised shelf space allocation problem with additions that address more practical scenarios in the retail sector, rationalizing this issue. They developed a combination of heuristics in a 5-phase "Squeaky Wheel" optimization with a local search technique to generate high-quality solutions to the problem [7].

Although marketing factors' elasticity can be fixed beforehand with known values, the demand function can readily accommodate them. The theory regarding self-service grocery retail stores posits that product demand is influenced by the extent of display exposure. It is hypothesized that this promotional structure can alter consumers' brand preferences [7]-[9]. Thus, in the demand function, only the product's direct spatial elasticity is often taken into account. Several strategies were given to solve the linear model [10]-[11].

This behavior reflects aggregated substitution effects, influencing overall demand patterns rather than just individual customer experiences at the store. Consequently, the initial assortment decision must account for potential substitution to accurately forecast demand and optimize inventory levels.

Metaheuristics are problem-solving techniques that aim to find approximate solutions to complex optimization problems, particularly when exact methods are impractical. These methods are often used to tackle large-scale, difficult problems by exploring various strategies and approaches to find near-optimal solutions efficiently.

The researches in [12] provided a comprehensive overview of meta-heuristic methods. Among the many types of metaheuristics are greedy random adaptive search procedures, neural networks, constraint logic programming, natural evolutionary computation, non-monotonic search strategies, space-search techniques, simulated annealing, tabu search, threshold algorithms and their hybrids, and neural networks [12].

The researches in [13] proposed to use a genetic algorithm to improve the retail shelf-space configuration instead of a heuristic approach, building on the genetic algorithm shelf-space research stream [13]-[16]. The suggested meta-heuristic technique has the following benefits: (1) it involves less computational work; and (2) managers can apply the solution obtained directly to the retail shelf space.

The researcher in [16] used a population-based solution or genetic algorithm and concluded that a metaheuristic outperformed a heuristic approach. On the other hand, the simulation makes the assumption that the product profit is independent of the horizontal shelf location inside a shelf section [16].

The researcher in [17] in their research grounded on the work of [16]. The researcher in [17] presented a hyperheuristic approach, such as a fast variant of the variable neighbourhood search and the reduced variable neighbourhood search. A commonly reduced variable neighbourhood search is beneficial when a local search is extremely costly. If random points are chosen from the current's nearby solutions and no descent is performed, the reduced variable neighbourhood search method is achieved [17].

The research [18] emphasized the principles and aims of space management in retailing, paying specific attention to space management activities at the category, segment, and brand levels. The goal was to assist retailers in navigating the retailer-imposed category management.

These advancements in metaheuristic techniques highlight the growing interest and potential of these methods in optimizing complex problems, including retail shelf-space allocation. By incorporating genetic algorithms and hyperheuristics, researchers have been able to enhance the effectiveness and efficiency of solution methods, reducing the computational burden and providing more practical, implementable results for managers. This progression in metaheuristic application allows for more refined, cost-effective approaches to shelf-space configuration, offering valuable insights for the retail industry.

Both assortment planning and shelf space allocation are critical in ensuring that a distribution centre operates efficiently and that products are delivered to the right place at the right time. Proper assortment planning helps ensure that distribution centres are stocked with the right products, while effective shelf space allocation maximizes the visibility and sales potential of those products. Together, they contribute to a smoother flow of goods, better customer satisfaction, and improved profitability across the supply chain.

3. Problem statement

The research focuses on the shelf space allocation problem (SSAP) in distribution centres and retail stores, analyzing the benefits of vertical and horizontal categorization for item (product) display. Vertical categorization enhances visibility, customer experience, and space utilization, while horizontal categorization increases exposure, navigation, and the promotion of key products. Combining both strategies improves customer experience and brand visibility. Products can be categorized by their specific attributes, like weight or perishability, and need to be stored appropriately to avoid risks like contamination or confusion. Clear categorization, product orientation, and rack dividers aid the organization. Retail managers must also consider historical sales data for better stock management and forecasting.

The goal of the SSAP under investigation is to maximize profit or product movement. To achieve this, retailers must determine the shelf placement for each product based on its vertical and horizontal categorization. Vertical and horizontal categorizations guide the most effective placement strategy to minimize retrieval times, ensuring products are positioned for maximum accessibility and operational efficiency. This includes deciding how many stock-keeping units (SKUs) to assign per shelf, the product orientation (front, side, or top), and addressing various constraints such as shelf, product, multi-shelf, and category-specific limitations.

The criterion of the SSAP is to maximize the profit of each SKU placed on each shelf. The core constraints related to SSAP can be explained as follows.

The shelf constraints: each product must fit within the shelf's length, height, and depth, ensuring the product's dimensions are compatible with the available shelf space.

The product constraints. Products must be placed on the shelf. There is a specified range for the number of SKUs allowed for each product on the shelf. Each product must have a designated orientation (front, side, or top), and only one orientation can be applied per product. Products requiring separate storage must be placed on different shelves. Incompatible products should not be placed next to each other, but if marked compatible, they must be stored together on the same shelf. The placement of products must align with their respective SKUs.

The multi-shelf constraints. Products can be placed on a specific number of shelves, with a defined minimum and maximum number of shelves allowed. There are storage limits when a product is distributed across multiple shelves, and the shelves should be placed near one another for efficient access.

The category constraint. Shelf and product compatibility must align according to their category tags. A minimum size for product categories must be maintained if products from the category are

placed on a shelf. Products within the same category should be evenly distributed across shelves to maintain balance and organization.

The decision variables constrains. The placement of each product on the shelf. The number of SKUs allocated to that product. The product orientation (front, side, or top) while placing it on the shelf.

4. Flower-cutting heuristics for the SSAP

We introduce novel flower-cutting heuristics that aim to address the challenges of solving SSAPs efficiently by systematically reducing the solution space while retaining high-quality results. The methodology involves two heuristic variants, each with a unique approach to sorting and selecting product allocations. Here's a summarized breakdown of the process.

The core concepts are shelf allocation, and product orientation and key metrics.

The shelf allocation and product orientation: products on shelves are assigned positions (front-facing, side-facing, top-facing) or do not place on the shelf at all. Each shelf allocation sequence encodes the placement and orientation of products.

The key metrics: total profit is the sum of profits from all shelves. Total width is the maximum cumulative width of products in a category. Profit ratio is the profit relative to space usage, excluding empty shelf space.

To decide a problem we use a heuristic workflow.

Problem definition and objectives: define SSAP constraints, profit maximization criteria, and success metrics such as accuracy (profit ratio), estimate the number of solutions, and computational time.

Simplified problem structure: products are allocated within categories individually before being combined across categories, i.e. prepare the parts of the solution for each single category.

Iterative optimization: parameters are adjusted to refine the solution set, focusing on reducing computational effort while preserving near-optimal results.

We state following Implementation highlights. The "flower garden" analogy visualizes the solution space. Each "flower" represents a potential solution. "Clearings" are profitable regions of the solution space. The "basket size" represents the number of solutions to be generated, which is the termination criteria. Parameters guide the selection of flowers (solutions) to focus on the most profitable options.

The optimization process should take into account following aspects. Initial heuristics are tested and evaluated against benchmarks, with parameters fine-tuned to balance solution quality and computational efficiency. Through iterations, the algorithm narrows down solutions using predefined rules, systematically eliminating near-duplicate or suboptimal configurations. A stopping criterion (e.g., basket capacity) ensures the process halts when acceptable resource utilization is achieved.

Tuning parameter roles: parameters of flower clearing forming: 1-4, parameters of moving along the selected flower clearings: 5-10, parameters of the interval between cut flowers on the selected clearings: 11-14, parameters of the flowers to be cut: 15-17.

Let consider the tuning parameter description.

Parameter 1 (focus on the maximum category width before forming product allocations). It limits the category width for product allocations, ensuring that the other categories can achieve high-value configurations.

Parameters 2 and 3 (focus on the number of products that can be placed on the shelf before forming product allocations). They form the number of product allocations per category, excluding low-value product allocations, which could appear in future steps.

Parameter 4 (focus on the profitable groups of products to be placed on the shelf). It establishes base filters for allowable product combinations on each shelf. It ensures only viable initial configurations are considered, reducing unnecessary allocations.

Parameters 5, 6 (focus on the category width threshold after forming product allocations). They cap the number of product allocations per category, focusing on the most promising options within each.

Parameter 8 (focus on the sorting order limiting the number of product allocations on the shelf). It defines the sequence for sorting product allocations, prioritizing based on category width $\uparrow$, category profit $\downarrow$ (for heuristics H1) and category profit $\downarrow$, category width $\uparrow$ (for heuristics H2).

Parameter 10 (focus on the sorting order limiting the number of product allocations in the category). It defines the sequence for sorting product allocations, prioritizing based profit ↓, profit ratio ↓(for heuristics H1) and profit ratio ↓, profit ↓(for heuristics H2).

Parameter 11(focus on the product allocation diversity control on the shelf). It ensures that a predefined diversity threshold is met across product allocations formed on the shelf.

Parameter 13 (focus on the product allocation diversity control on the category). It ensures that a predefined diversity threshold is met across product allocations formed on the category.

Parameters 12, 14 (focus on limiting the product allocation after applying parameters 11, 13). They prevent over-consolidation by maintaining a definite number of product allocation options, which is essential for scenarios requiring flexibility in shelf configuration. They enable the fine-tuning of priorities based on profitability for specific product allocations.

Parameters 15, 16 (focus on the category-based profit limits). They process the product on shelves as clusters based on profit similarity. They focus optimization efforts on clusters with the highest potential impact, eliminating the low-profit product allocations.

Parameter 17 (focus on the lower bound of accepted total profit). It establishes the minimum profit for the solution to qualify, ensuring the profitability of the result.

Let consider the tuning grouping parameter roles and impact.

Parameter 7 (focus on maximum total profit per total width). It limits product allocations by considering only one product allocation for each total width, selecting the one with the maximum total profit. It balances computational efficiency and solution diversity. It enables heuristics for faster solution generation while maintaining near-optimal results.

Parameter 9 (focus on minimum total width per profit and profit ratio). It limits product allocations by considering only one product allocation for each combination of total profit and profit ratio, selecting the one with the minimum total width. It is particularly effective in accelerating convergence for larger problem instances. It significantly minimizes the solution space, allowing for efficient handling of large-scale problems.

Results and deployment. The heuristics demonstrate scalability, handling larger instances while maintaining solution diversity. The tuning parameters allow us to achieve significant reductions in solution space without sacrificing profitability. Final heuristics are validated documented, and could be integrated into retail space management systems.

Figure 1 depicts the flower garden analogy, focusing on the specific flower patches where the gardener (representing the heuristic) selects and cuts flowers, symbolizing potential solutions. In the real solution space, multiple flower patches may be chosen, each defined by unique characteristics.

The selection process begins with identifying a threshold height above which flowers are deemed suitable for cutting and placing in the basket. Within each selected patch, only certain flowers are cut and spaced apart by intervals that reflect the heuristic criteria. These intervals, along with the height thresholds and the patch widths, vary between patches, emphasizing the diversity of potential solutions. Flowers in unselected patches are ignored, even if their heights surpass the thresholds of other patches, focusing the effort on promising areas.

The objective is to prioritize patches with the largest and most profitable flowers, ensuring no valuable patch is overlooked. The gardener's task is unconcerned with the distances between patches; instead, the focus remains on harvesting the most profitable flowers within the chosen patches.

The algorithm's computational time mirrors the gardener's efficiency, relying solely on the time spent assessing and cutting flowers in the selected patches while disregarding unselected patches. This visualization underscores the heuristic's ability to streamline the solution space, concentrating only on areas with the highest potential for optimal outcomes.

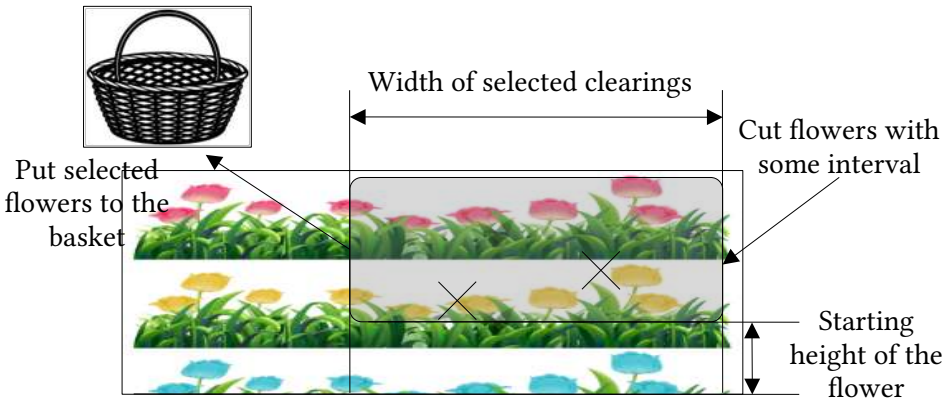

Figure 1: Looking for patches to cut flowers and cutting flowers with some intervals

5. Experiment

The study evaluates the performance of two heuristics (H1 and H2) across a range of test scenarios with varying product counts (10, 15, 20, 25, and 30) and shelf widths (250, 375, 500, 625, and 750). The performance of the developed heuristics for solving the SSAP was evaluated through experiments comparing their solutions to the optimal results from the CPLEX solver.

The study focused on the best-performing parameter configurations, identified through systematic tuning, to ensure high-quality solutions. Key metrics such as solution quality, computational time, and proximity to optimality were analyzed. The results provide insights into the efficiency of the heuristics and their potential for improving shelf space management in complex scenarios.

The computer parameters were: processor: AMD Ryzen 5 1600 Six-Core Processor 3.20 GHz, system type: 64-bit Operation System, x64-based processor,. RAM: 16 GB, operation system: MS Windows 10.

Table 1 presents the average performance of the developed heuristics. Across all test scenarios, heuristic H1 consistently achieved near-optimal profit ratios, averaging 99.85%, with computation times ranging from 0.05 to 5.60 minutes. Heuristic H2 displayed slightly higher computation times, ranging from 0.05 to 7.01 minutes, but similar profit ratios, averaging 99.86%. The CPLEX solver was effective for smaller cases, with times as low as 0.36 seconds, but scaled less efficiently; its maximum computation time was 6.48 seconds.

In terms of performance consistency, both heuristics (H1 and H2) consistently achieve high-profit ratios, with most values at or near 100%. This indicates their effectiveness in maximizing profit regardless of the number of products or shelf width. When talking about the efficiency of heuristics, it can be observed that H1 generally has faster computation times than H2. As the number of products and shelf width increase, computation times for both heuristics and CPLEX increase, although CPLEX exhibits significant variation in computation time.

Table 1
The average performance of the developed heuristics

Products	Average profit ratio of H1	Average profit ratio of H2	Average time of H1 [min]	Average time of H2 [min]	Average time of CPLEX [s]
10	100.00%	100.00%	0.33	0.33	0.52
15	99.96%	99.96%	0.78	1.52	0.75
20	99.99%	100.00%	3.21	4.39	1.07
25	99.85%	99.87%	2.92	3.87	1.79
30	99.43%	99.45%	2.52	2.81	3.68

The next phase of the experiment focuses on evaluating the impact of grouping tuning parameters. Parameter 7 prioritizes generating a single product allocation for each total width that maximizes the total profit among the available options. Parameter 9, on the other hand, focuses on

generating a single product allocation for each total profit and profit ratio that minimizes the total width among the available options.

Table 2 displays the number of product allocations (the number of SKUs put on the shelf) that correspond to the number of generated shelf allocations if the product is put on the shelf). The number of product allocations is presented after applying the initial product allocation parameters 1-4 and the minimum and maximum width parameters (parameters 5 and 6). So, there is not a complete solution space, but there is already a reduced one. Although this is not the entire number of potential solutions, it is clear that even after reduction, there are still a lot of product allocations that need to be examined. These product allocations will be used to determine the ultimate solution.

The numbers of shelf allocations for 10, 15, 20, 25, and 30 product sets varied from 3 to 6, from 3 to 36, from 3 to 79, from 4 to 106, and from 4 to 119 for each product set, respectively. The numbers of product allocations for 10, 15, 20, 25, and 30 product sets varied from 24 to 2 879, from 54 to 23 609, from 42 to 57 289, from 48 to 728 143, and from 65 to 87 881 for each product set respectively. Despite the fact that the presented numbers of product allocations are calculated after the reduction solution space parameters, we can't check all of them; therefore, further reduction solution space is still needed.

Table 2
Numbers of generated shelf allocations and product allocations in heuristics H1, H2

Products	Shelf width	Number of shelf allocations				Number of product allocations			
		Shelf 1	Shelf 2	Shelf 3	Shelf 4	Shelf 1	Shelf 2	Shelf 3	Shelf 4
10	250	4	6	4	6	24	145	140	80
	375	4	6	4	6	26	414	426	279
	500	4	6	4	6	30	950	956	688
	625	3	6	4	6	28	1 782	1 771	1 359
	750	3	6	4	6	26	2 870	2 879	2 361
15	250	3	36	17	24	57	271	791	120
	375	3	35	17	24	76	1 480	3 241	397
	500	3	35	17	24	54	3 213	5 454	681
	625	3	35	17	23	84	4 708	13 510	949
	750	3	34	17	23	88	9 480	23 609	1 695
20	250	3	68	62	48	66	1 524	6 377	3 346
	375	3	79	69	59	90	7 312	29 609	14 350
	500	3	35	30	24	109	2 855	9 802	5 628
	625	3	35	30	24	42	5 913	14 682	7 860
	750	3	35	30	24	50	44 254	57 289	23 794
25	250	4	84	63	62	48	1 385	6 931	1 035
	375	4	106	69	74	48	3 040	19 743	2 378
	500	4	79	61	59	71	8 860	43 337	5 237
	625	4	82	61	62	74	23 257	148 586	15 541
	750	4	64	50	53	65	83 946	728 143	25 577
30	250	5	119	105	91	65	1 550	1 885	2 167
	375	4	58	38	48	75	4 762	3 447	752
	500	4	59	24	38	110	5 639	5 834	8 879
	625	4	51	31	38	83	10 105	7 789	15 989
	750	4	71	24	45	120	11 500	87 881	6 521

Table 3 presents the number of product allocations after applying grouping parameter 7 to all instances except the smallest 10 product sets. The values in Table 3 could be compared to the values in Table 2. Therefore, the product allocations given here are also achieved after applying all previous reducing space parameters, i.e. the initial product allocation parameters 1-4 and the minimum and maximum width parameters (parameters 5 and 6). The number of product allocations that will be processed after applying parameter 7 is limited by parameter 8. The amount of checked product allocations limited by the parameter 8 was shown in Table 2.

Table 3 shows how much the solution space was reduced with the help of parameter 7. So, on average, the number of product allocations on each shelf was 56, 1 937, 870, 1 139. These numbers varied from 22 to 117 for the 1st shelf, 661 to 3 512 for the 2nd shelf, 110 to 1 692 for the 3rd shelf, 252 to 2 216 for the 4th shelf.

Table 3
Numbers of product allocations after applying grouping parameter 7 in heuristics H1, H2

Products	Shelf width	Shelf 1	Shelf 2	Shelf 3	Shelf 4
15	250	35	661	110	252
	375	40	1 393	262	673
	500	26	1 196	257	624
	625	36	1 425	381	764
	750	38	1 651	459	884
20	250	22	1 458	938	697
	375	38	1 964	1 322	1 185
	500	52	1 242	915	790
	625	40	1 325	955	915
	750	48	1 528	1 113	991
25	250	48	2 544	751	917
	375	48	3 512	1 266	1 546
	500	71	3 278	1 544	2 131
	625	74	3 046	1 692	2 216
	750	65	2 739	1 362	1 972
30	250	63	1 382	1 374	1 184
	375	72	1 667	485	1 098
	500	106	2 040	753	1 115
	625	81	1 634	741	1 226
	750	117	3 054	720	1 592
Minimum		22	661	110	252
Average		56	1 937	870	1 139
Maximum		117	3 512	1 692	2 216

Following the application of grouping parameter 9, the number of created product allocations (the number of SKUs put on the shelf) is displayed in Table 4. Only large test instances of 25 and 30-product sets were subject to this parameter. The values attained were used for subsequent actions.

Even though Table 3 shows nearly equal numbers of product allocations on the shelves for 15-20 and 25-30 product sets, the issue arises when the new category (25-30 product sets) is added, making the reduction grouping parameter 9 necessary. Not every product allocation obtained after grouping is used for subsequent phases. Parameter 10 sets a limit on how many product allocations can be handled following the application of parameter 9.For medium (15-20 product sets) instances parameter 10 was utilized without the use of parameter 9. For small (10 product sets) instances, parameters 9 and 10 were not used.

It could be observed that for the 1st category for 25-product set on the 250 cm shelves, the number of product allocations was reduced from 1 074 107to 742 after applying this parameter. For most of these 3-category instances, the number of product allocations has been significantly reduced from millions and thousands to thousands and hundreds, which is a forward-looking improvement of the main algorithm. The procedure for looking for further solutions is streamlined, and efficiency is increased by this modification.

Table 4
Numbers of product allocations before and after applying grouping parameter 9 in heuristics H1, H2

Products	Shelf width	Before grouping			After grouping		
		Category 1	Category 2	Category 3	Category 1	Category 2	Category 3
10	250	703	680	-	-	-	-
	375	3 057	908	-	-	-	-
	500	3 478	2 580	-	-	-	-
	625	3 852	296	-	-	-	-
	750	394	440	-	-	-	-
15	250	17 047	12 318	-	-	-	-
	375	168 557	41 100	-	-	-	-
	500	11 086	583	-	-	-	-
	625	53 101	7 488	-	-	-	-
	750	98 474	18 904	-	-	-	-
20	250	2 397	25 749	-	-	-	-
	375	3 536	1 100	-	-	-	-
	500	34 906	44 365	-	-	-	-
	625	12 145	59 414	-	-	-	-
	750	6 021	17 989	-	-	-	-
25	250	1 074 107	4 571	4 464	742	656	492
	375	437 455	186 094	3 119	748	681	691
	500	128 524	10 056	45 370	474	443	998
	625	147 050	22 473	102 114	422	455	616
	750	130 019	11 815	4 391	340	314	391
30	250	371 902	898	2 727	1 082	308	359
	375	408 315	42 091	11 362	1 507	2 383	592
	500	246 462	21 360	4 780	2 465	2 590	547
	625	22 925	26 699	5 021	659	1 581	547
	750	20 036	702	15 679	640	402	1 355
Minimum		394	296	2 727	340	308	359
Average		136 222	22 427	19 903	908	981	659
Maximum		1 074 107	186 094	102 114	2 465	2 590	1 355

6. Discussion

As a result of conducted experiments we obtain following observations.

The reduction in solution space. Both grouping parameters (7 and 9) significantly reduce the number of generated product allocations, which directly minimizes the solution space, enhancing computational efficiency. Parameter 7: By focusing on maximizing the total profit for each total width, the number of product allocations was drastically reduced across all shelf widths. For instance, at the 3rd shelf for 25 products and a shelf width of 750 cm, the number of product allocations decreased from 728 143 to 1 362. Parameter 9: Targeting the minimum total width for each total profit and profit ratio resulted in a substantial reduction in the solution space. For example, at 25 products and a shelf width of 250, the number of product allocations in Category 1 dropped from 1 074 107 to 742, Category 2 from 4 571 to 656, and Category 3 from 4 464 to 492.

The generation of near-optimal results. Despite the reduction in solution space, both parameters retained the heuristics' ability to generate solutions close to the optimal, as demonstrated earlier in their high-profit ratios. Parameter 7: Ensures near-optimal results by prioritizing the maximum

profit allocation for each shelf width, maintaining the quality of solutions while drastically reducing complexity. Parameter 9: Focuses on minimizing total width for specific profit categories for each total profit and profit ratio, aligning with the goal of achieving efficient space utilization without compromising profitability.

The grouping tuning parameters. The number of product allocations after applying Parameter 7 was reduced by approximately 60–90% in most cases while preserving diversity across profit categories. Parameter 9 achieved reductions of up to 95% in certain scenarios, particularly in high-complexity instances like 30 products or large shelf widths, enabling faster solution convergence.

The effectiveness across problem scenarios. The grouping tuning parameters demonstrated scalability across varying problem sizes (e.g., 10–30 products) and shelf widths (250–750). This confirms their adaptability and robustness in handling different complexities inherent in the SSAP.

The overall impact of grouping tuning parameters. The application of grouping tuning parameters (7 and 9) is instrumental in significantly reducing computational demands while maintaining solution quality. This allows the heuristics to remain effective in generating near-optimal allocations with a fraction of the original solution space. These parameters enable a more practical approach to solving large-scale SSAP problems, making them suitable for real-world applications.

7. Conclusion

In this research, concepts of item categorization and allocation on the warehouse racks are considered. It's critical to arrange items on warehouse or distribution centre racks according to the correct categories. The investigated SSAP approach allows organizing the racks simultaneously vertically and horizontally according to the category or product type. The proposed model deals with shelf space optimization by appropriately arranging product categories maximizing the gained profit or movement of the products to make the most of available shelf space while adhering to the following categories of constraints: shelf, product, multi-shelves, and category constraints. It makes it possible to efficiently distribute shelf space in a way that optimizes operational effectiveness and guarantees the integrity of the stored goods by combining these constraints. Furthermore, our approach extends beyond traditional shelf allocation methods by considering the diverse needs of different products. Therefore, in the developed model, we include two types of such products: (1) incompatible products, which must not be placed one next to the other on the same shelf, and (2) products requiring separate storage, which must not be placed on the same shelf.

In order to optimize space usage and uphold safety regulations in the warehouse setting, decisions on shelf structure, spacing, and weight distribution can also be made based on the products' heterogeneous character. Some products have a specific packaging shape, size or stocking possibilities, which may determine how best to place them and which orientation is better. If there is a grouping of products by category on the shelf, then it is advisable to display the products so that their name or main element is visible at first glance of the picker at this category on the rack. In this research, we use three orientations of the product on the shelf: front, side, and top.

In this research, we propose flower-picking heuristics with tuning parameters to deal with the described SSAP. Performance metrics include the profit ratio, computation times for the heuristics, and the computation time for the CPLEX solver, which serves as a benchmark for exact solutions.

The profit ratios remain consistently high across all scenarios, with averages near 99.85% for H1 and 99.86% for H2. Computation times show significant variability, with H1 taking up to 5.60 minutes and H2 taking up to 7.01 minutes in the worst case. The fastest computation time was 0.05 minutes for both heuristics.

Comparing the heuristics performance with CPLEX, it could be observed that the CPLEX solver is faster in small-scale scenarios but does not scale as efficiently with an increasing number of products or shelf width. The heuristics are more practical for larger problem sizes due to their ability to deliver optimal or near-optimal solutions in a shorter time frame.

The study also investigates the impact of two grouping tuning parameters on the number of generated product allocations and their influence on space utilization, accessibility, and operational efficiency. Parameter 7 represents a strategy that considers only one product allocation with the maximum total profit for each total width. Parameter 9 represents a strategy that selects only one product allocation with the minimum total width for each total profit and profit ratio.

The use of grouping tuning parameters results in fewer product allocations. These reductions of solution space, coupled with the maintenance of solution quality, underscore the value of grouping as an efficient strategy for tackling the investigated SSAP.

Applying Parameter 7 reduced the number of product allocations by approximately 60–90% in most cases while maintaining diversity across profit categories. Parameter 9 achieved reductions of up to 95%, especially in high-complexity scenarios such as instances with 30 products or large shelf widths, significantly accelerating solution convergence.

There are several ways in which future research can enhance its effectiveness. Firstly, it is real-time optimization in dynamic environments: Future studies could focus on optimizing product allocation in environments that are constantly changing, such as warehouses with high product turnover or seasonal demand fluctuations. This would involve developing heuristics that adjust automatically based on real-time data, such as stock levels, order frequency, or product shelf-life. Secondly, it is a multi-objective optimization. Research could explore models that balance multiple objectives, such as reducing operational costs, improving product accessibility, and maximizing profitability. This would involve developing complex heuristics or hybrid algorithms that can handle conflicting goals efficiently.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Analysis of Methods and Implementation of a Modern Technology Stack for Increasing the Productivity of Websites

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Abstract

This study focuses on improving the performance and scalability of web applications by leveraging modern architectural solutions and optimization techniques. The research explores key aspects such as the Model-View-Controller (MVC) pattern, process clustering, and database performance under high loads. The researchers conducted experimental tests to evaluate system efficiency and analyzed load-balancing algorithms to improve scalability. The study resulted in developing a web application that supports MVC, clustering, and Cross-Origin Resource Sharing (CORS), demonstrating its practical applicability in educational platforms, e-commerce, and CRM systems. The implemented solution performed efficiently under high-load conditions, significantly improving response times and handling multiple simultaneous requests. The findings emphasize the importance of modern optimization techniques in ensuring high performance, improving user experience, and increasing conversion rates.

Keywords

Load optimization, clusters, MVC, web application, performance, load balance, response time.

1. Introduction

Web technologies, which have become an integral part of the modern world, open up great opportunities for developing interactive solutions in various areas of life. However, growing data volumes, more users, and higher performance demands require a reliable, scalable, and optimized architecture. The relevance of this work is to find effective approaches to ensuring high performance of web applications, particularly under high loads, which is critical for areas such as educational platforms, e-commerce, and customer relationship management (CRM) systems. The aim of the study is to develop a high-performance and scalable solution that ensures stable operation even under high load conditions. To achieve this goal, the study focuses on key aspects such as efficient server cluster management, code organization using the Model-View-Controller (MVC) architecture, configuration of security mechanisms like Cross-Origin Resource Sharing (CORS) [1], and optimization of database interaction. The course also explores load-balancing methods and approaches to increasing the interactivity of web applications.

2. Problem Statement

One key indicator of a website's performance is its loading speed, which depends on various factors. In this study, the authors hypothesize that using modern technologies—such as Node.js [2] for server-side request processing and MongoDB [3] for data storage—can significantly improve web application performance under high loads. The architecture of a web application—particularly the use of the MVC pattern—directly influences its scalability and request processing speed. Using the MVC architecture alongside PM2 clustering is expected to reduce response times, improve the system's ability to handle simultaneous requests, and enhance security through CORS.

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To test the hypothesis, the authors will use research methods including field observation, testing, and case studies. First, we will conduct experimental testing of the web application with different technology stacks and architectural solutions. The authors will compare the test results to determine whether they confirm the hypothesis and to assess improvements in response time and request processing. The study will record specific data, such as response time in milliseconds and the number of simultaneous requests, for performance analysis.

2.1. Modern methods for optimizing website performance

In order to store static website resources closer to users and cut down on page load times by doing away with the need to send requests to a central server, a content delivery network (CDN) is a globally distributed network of servers. A CDN's distributed architecture offers several advantages, including faster content delivery, reduced server load, and better protection against denial-of-service (DDoS) attacks. Optimizing images is one of the easiest and most efficient methods for making web pages smaller. File sizes can be decreased without sacrificing quality with the use of programs like TinyPNG [4], ImageOptim [5], and WebP [6] formats. Furthermore, minifying code and optimizing JavaScript and cascading style sheet (CSS) files can significantly improve page rendering speeds. Browsers can load distinct sections of a webpage independently thanks to asynchronous loading, which guarantees faster access to visible content. Web applications run faster when caching is implemented on both the client side (using Local Storage or Cache API) and the server side (using Redis or Memcached). This reduces the number of repeated requests.

2.2. Analysis of trends in web development

Web development trends of the present day include:

- The rise of single-page applications (SPAs);
- Frameworks such as React, Angular, and Vue.js enable the creation of dynamic single-page applications that offer a more engaging user experience. For commercial projects that require fast performance and visibility, Server-Side Rendering (SSR) is especially useful as it boosts page load speed and enhances search engine optimization (SEO). Microservice architecture enhances scalability and flexibility by allowing the independent development of application components [7].
- Automation and CI/CD: Tools like Jenkins and GitLab CI/CD simplify testing and deployment, accelerating development and ensuring smoother releases [8].

3. Node productivity improvement

To demonstrate how productivity issues can arise, it is necessary to first illustrate these challenges before proposing methods to increase productivity (Figure 1).

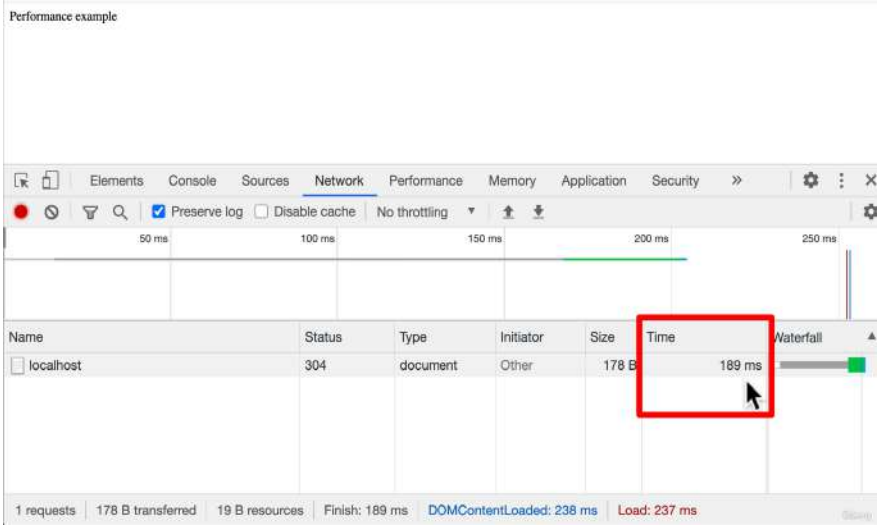

Figure 1: Website rendering speed result

Table 1
Comparison of Technologies for Accelerating Website Performance

Criterion	Node.js (my stack)	React	Angular	Vue.js
Purpose	A server-side platform for request processing, scaling, and database operations improves performance and scalability.	Client-side framework for building UI.	Client-side framework for building UI.	Client-side framework for building UI.
Server-Side Performance	Performance is high due to the asynchronous architecture and clustering (e.g., via PM2).	Not applicable (client-side framework).	Not applicable (client-side framework).	Not applicable (client-side framework).
Client-Side Performance	Not applicable (server-side technology).	High due to Virtual DOM.	Moderate due to full-fledged framework.	High due to lightweight architecture.
Scalability	Performance is high due to clustering (using the Node.js cluster module) and cloud solutions (such as MongoDB Atlas).	Depends on this application architecture.	Depends on this application architecture.	Depends on this application architecture.
Request Optimization	Performance is high due to asynchronous request processing and MongoDB, which enables fast data operations.	Not applicable (client-side framework).	Not applicable (client-side framework).	Not applicable (client-side framework).
SEO	Supported via Server-Side Rendering (SSR) using libraries (e.g., Next.js).	SSR is supported via Next.js.	SSR is supported via Angular Universal.	SSR is supported via Nuxt.js.
High-Load Performance	Efficiency is high due to clustering and PM2 for process management.	It depends on the server-side architecture.	It depends on the server-side architecture.	It depends on the server-side architecture.
Flexibility	High due to modular architecture and support for various databases (MongoDB, PostgreSQL).	High due to component-based architecture.	Moderate due to full-fledged framework structure.	High due to lightweight architecture.
Real-Time Support	Performance is high due to WebSockets and asynchronous event handling.	It requires additional libraries, such as Socket.IO.	It requires additional libraries, such as Socket.IO.	It requires additional libraries, such as Socket.IO.
Integration with Other Technologies	It offers easy integration with Express.js, MongoDB, PM2, and other server-side tools.	It allows easy integration with any server-side stack.	It allows easy integration with any server-side stack.	It allows easy integration with any server-side stack.

Typically, this request is completed in less than 20 milliseconds [9], as shown in Figure 1: Website rendering speed result. One challenge in this section, as well as in performance

measurements in real-world scenarios, is the variability in behavior based on different circumstances. Factors such as the operating system, running applications, CPU speed, and Node version can influence the outcomes. A performance code example highlights this variability. Both the CPU and the event loop experience significant load. Under such conditions, processing occurs at the maximum speed supported by the CPU [10]. The server cannot process additional requests until the delay function completes, which marks the end of the event loop. This phenomenon becomes evident when navigating to the root endpoints in one browser tab while simultaneously accessing the timer endpoints in another. The processing time, expected to be around 20 milliseconds, was significantly exceeded, taking six and a half seconds instead (Figure 2). This happens because the timer endpoint continues running even after switching to a different tab or clicking the "Refresh" button, taking about two and a half seconds. The blocking code causes the entire server to slow down, delaying the refresh of the second tab until the first has finished processing.

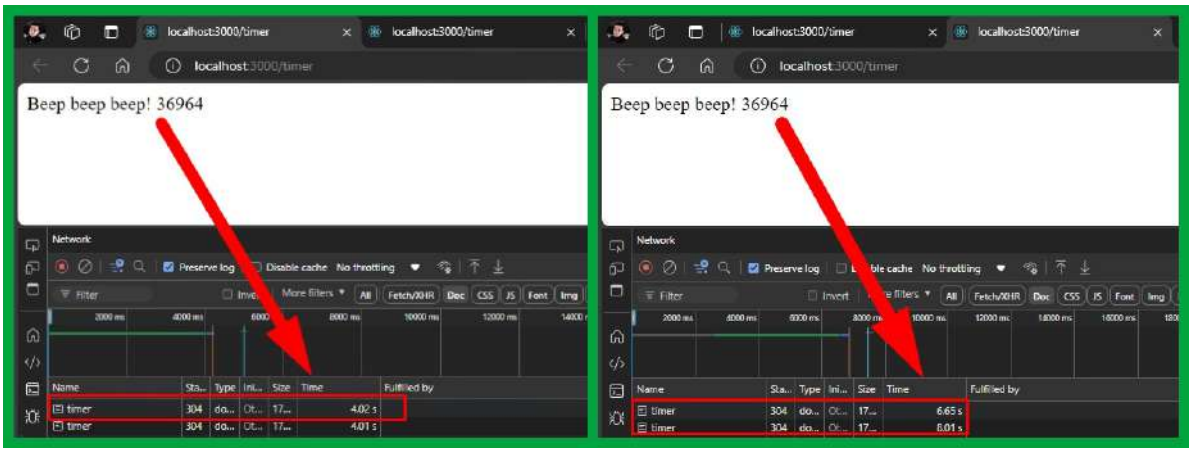

Figure 2: Time delay difference between first and second tab

The delay function simulates the worst possible blocking behavior by halting the event loop for several seconds. In real-world applications, response times should typically stay below 100 or 200 milliseconds. Research has examined how users perceive response times in web and application contexts. As early as 1968, researchers established that users perceive a response as instantaneous only if it occurs within 100 milliseconds [11]. Ensuring response times do not exceed this threshold is crucial. Additionally, response times longer than one second can disrupt the user's flow of thought and result in the loss of context for their intended action. Furthermore, the delay may disrupt the user's flow of thought, causing them to lose the context of their intended action. The number of users who remain on the site will probably gradually decrease if there are any increases last longer than a second. For many years, the basic rules for response times have not changed [Miller 1968; Card et al. 1991]:

- **0.1 second:** At this point, the user perceives the system as instantaneous and requires no additional feedback beyond showing the outcome.
- **1.0 second**: This is the maximum amount of time that a user can continue thinking without experiencing any delays, but they will be aware of them. For delays between 0 and 1 second, feedback is usually not needed; however, the user may no longer feel like they are interacting directly with the data.
- **10 seconds**: After this, it becomes difficult to maintain the user's interest in the interaction. For a longer wait.

3.1. Running multiple Node processes

In Node.js, multiple Node processes can run simultaneously, allowing them to share workloads in a way similar to a team working together toward a common goal. When operating servers, the system divides workloads into requests sent to the server. Rather than processing all incoming requests on a single Node process, the system can distribute the requests across multiple Node processes, each handling server procedures independently. These processes execute the same server code in parallel, functioning side by side. For example, a second Node process may handle the second request, while a third Node process handles a third request. Furthermore, each process is capable

can manage multiple requests simultaneously, even if the number of incoming requests exceeds the number of server processes. The critical advantage of this approach is the even distribution of workloads among the processes [12]. By using this technology, single-threaded Node applications can effectively utilize all of a computer's processors. As illustrated in Figure 3, modern computers typically feature multiple processor cores, enabling parallel execution of code without compromising the efficiency of processes running on other cores.

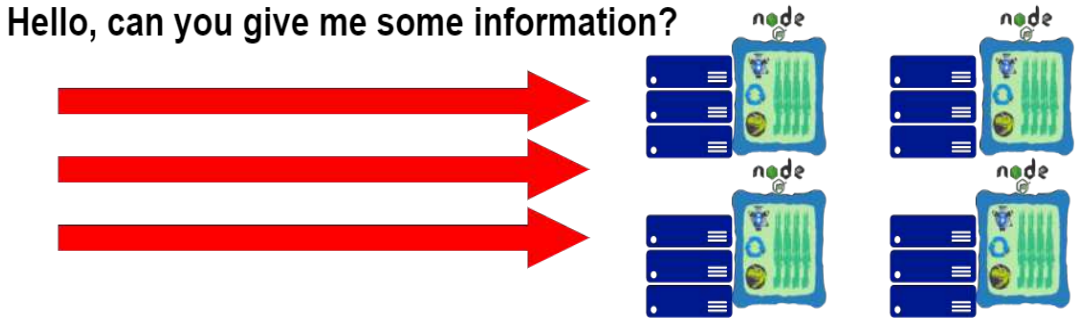

Figure 3: CPU multithreading demonstration

3.2. Node cluster module

The initial approach to improving node performance involves using the built-in node cluster module [13]. The cluster module enables the creation of copies of the node process, each executing server code in parallel and side by side. Figure 4 illustrates this process. When a node type is specified, the server starts the execution of the node application, creating a primary node process [14]. In the cluster module, this process called the controller process. The function called fork allows access. Whenever a worker function in the server file runs, the primary process creates a copy, known as a worker process. This function, fork, can be called multiple times. Furthermore, it is often preferable to create multiple worker processes attached to a single primary process.

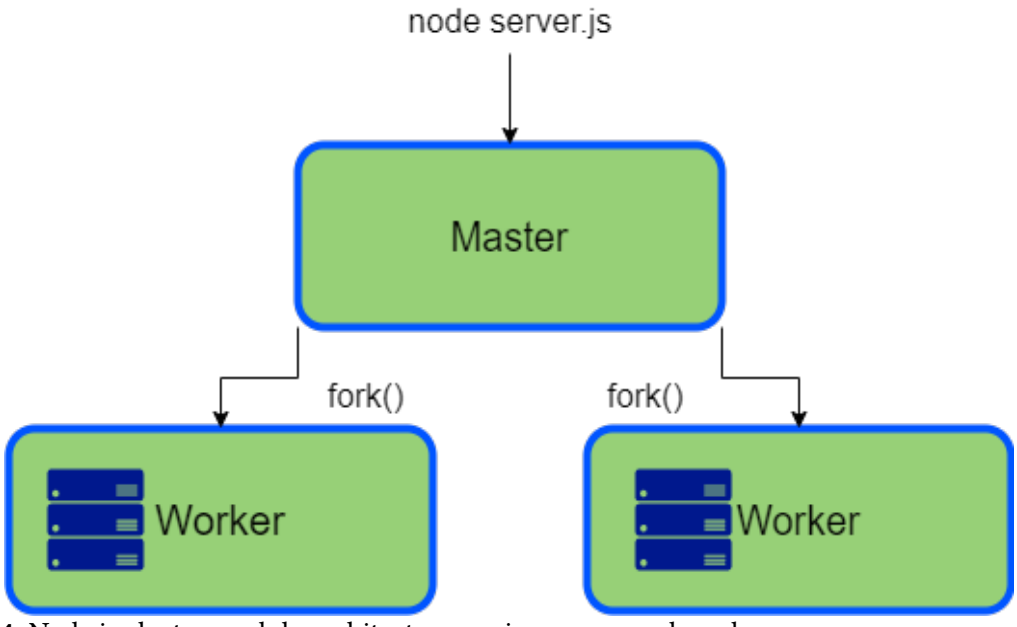

Figure 4: Node.js cluster module architecture, main process and worker processes

These workers handle the heavy lifting of accepting, processing, and responding to Hypertext Transfer Protocol (HTTP) requests. Each worker contains the necessary code to manage any server request, while the master coordinates the creation of these workers using the fork function.

This configuration contains three nodes, as the worker function runs twice. These include the master process (started by the running server). The fork function and JavaScript created two worker processes. These workers handle incoming requests in a round-robin fashion: the first worker receives the first request, the second worker receives the second, and so on. One of the simplest and

most equitable ways to divide the workload among employees is still the round-robin method, even though request processing times can differ. Nevertheless, on Windows, because of how the operating system handles processes, Node. JS leaves task distribution up to the system and does not ensure a rigorous round-robin method. Nevertheless, Windows still supports round-robin for load distribution.

3.3. Clustering in action

3.3.1. Proposed solution

Node.js, by default, runs on a single thread, which limits its ability to fully utilize multi-core processors. This can lead to utilize multi-core processors fully:

- Inefficient CPU Utilization: Only one CPU core is active, leaving the others idle;
- Bottlenecks in High-Load Scenarios. Long-running tasks can block the event loop, delaying the processing of other requests;
- Limited Scalability. A single process cannot handle a large number of simultaneous requests efficiently.

To address these issues, the Node.js cluster module creates multiple worker processes, allowing the application to:

- Distribute incoming requests across multiple CPU cores;
- Improve response times by parallelizing request processing;
- Scale horizontally by adding more worker processes as needed.

3.3.2. Implementation

Initialization of the Cluster Module:

- The built-in cluster module was imported and assigned to a constant;
- A primary process was created to manage worker processes [15].

Forking Worker Processes:

- The cluster.fork() method creates worker processes;
- Each worker process runs the same server code (server.js) and listens on the same port (e.g., port 3000).

Load Distribution:

- Incoming HTTP requests were distributed among worker processes using a round-robin approach;
- The master process coordinated the creation and management of worker processes [16–17].

3.3.3. Results and conclusion

- The application's response time under high load decreased from 6.5 seconds to 4 seconds;
- The application could handle eight simultaneous requests without performance degradation;
- The system utilized all available CPU cores, maximizing server performance.

Figure 5 illustrates the initialization of clustering and the creation of worker processes.

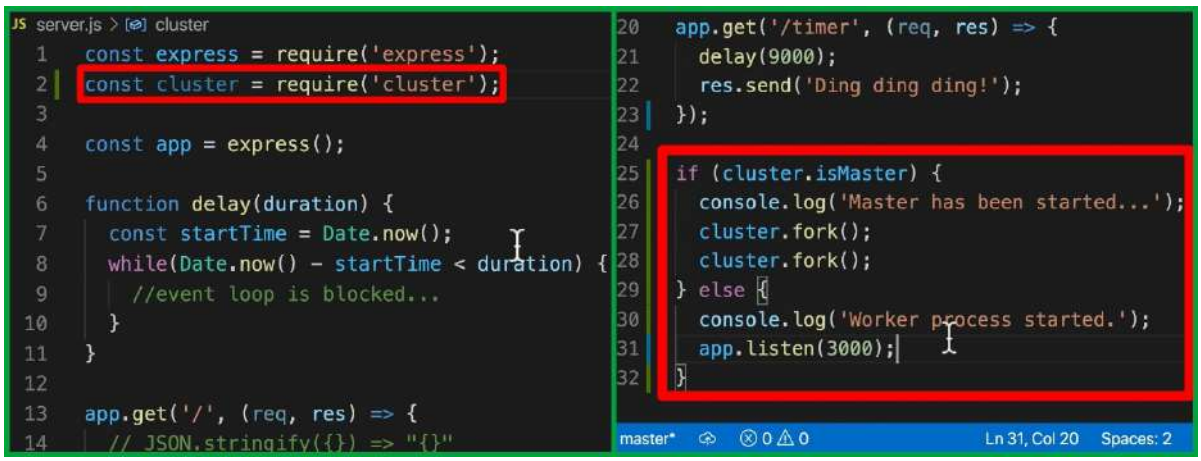

Figure 5: Initializing clustering and starting server processes

When testing server clustering, it is necessary to turn off the cache to ensure that Chrome executes requests without relying on cached data. The cache should be turned off in both tabs to achieve accurate results. Two requests are made in one tab to the timer endpoint, followed by a quick refresh of both the first and second tabs.

As shown in Figure 6, the first tab indicates that the connection is waiting. After nine seconds, the system returns a successful 200 response. Simultaneously, the second tab also receives the response, with both requests taking nine seconds to complete [18]. These requests ran in parallel on the computer, thanks to the presence of two processor cores, which allowed the processing to occur in two separate processes.

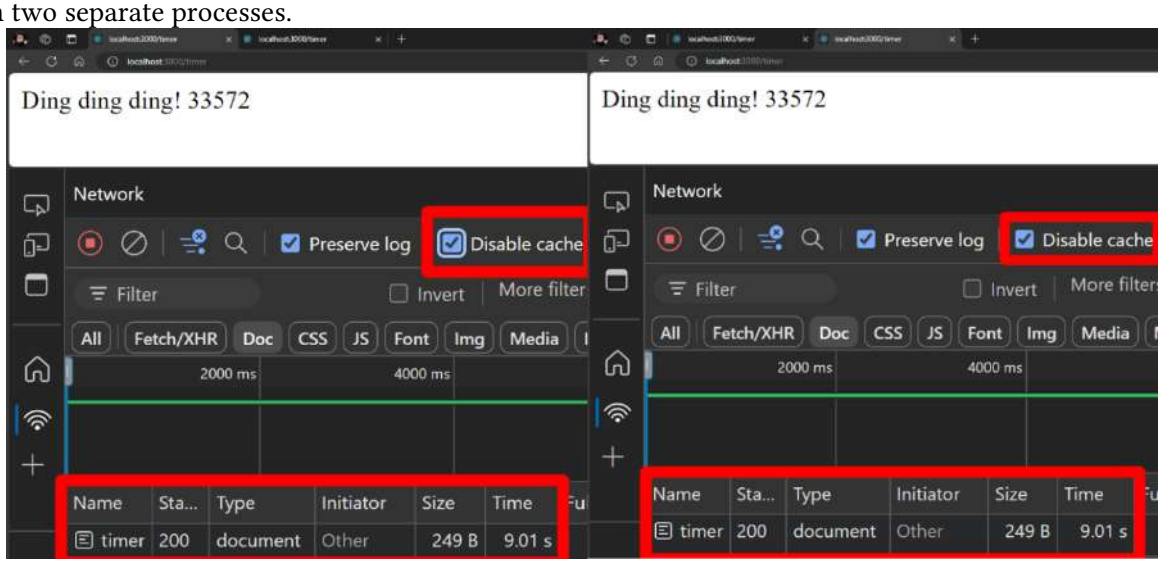

Figure 6: Parallel processing of timers using two physical computer cores

In Figure 7, the system sends a request to the timer endpoint in one tab and to the root directory in another. The request to the root directory returned almost immediately, within 27 milliseconds. This demonstrates that the route and endpoint are not required to wait for the timer to complete execution in the first tab. This behavior matches the intended functionality exactly.

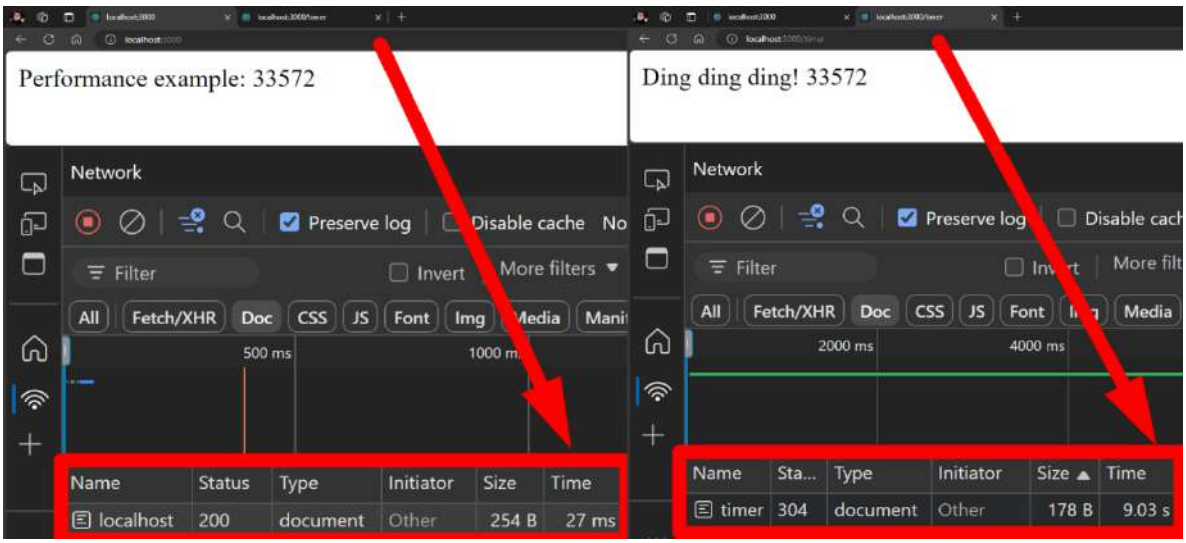

Figure 7: Comparing the root tab and the timer tab for performance at the same time

3.4. Maximizing cluster performance

3.4.1. Problem specification

While clustering improves performance, it has limitations:

- The system limits the number of worker processes to the number of CPU cores;
- Long-running tasks can still block worker processes, reducing overall efficiency.

3.4.2. Proposed Solution

To maximize cluster performance, we took the following steps
Dynamic Worker Creation:

- The number of worker processes was dynamically set based on the number of logical CPU cores available;
- This approach ensured efficient utilization of each CPU core.

3.4.3. Load balancing

- Requests were distributed evenly among worker processes using a round-robin strategy.

3.4.4. Performance monitoring

- We used the PM2 [19] tool to monitor and manage worker processes, ensuring high availability and automatic restarts in case of failures.

3.4.5. Implementation

Determining the Number of Workers:

- The OS (Operating System) module was used to determine the number of logical CPU cores [20];
- The number of worker processes was equal to the number of logical cores (e.g., eight workers for eight logical cores).

Handling High-Load Scenarios:

- Multiple requests were simulated to test the cluster's performance;
- The browser cache was turned off to ensure accurate measurement of response times.

Testing Parallel Processing:

- We sent requests to the /timer endpoint simultaneously across multiple browser tabs;
- Response times were measured to evaluate the cluster's ability to handle parallel requests.

3.4.6. Results and conclusion

- The cluster successfully processed eight simultaneous requests in 9 seconds, demonstrating efficient utilization of all CPU cores.
- Requests to the /timer endpoint returned consistent response times, even under high load.
- When the number of requests exceeded the number of worker processes, response times increased (e.g., from 9 seconds to 16 seconds for the fourth request).

Figure 8 shows that each tab has a network console open.

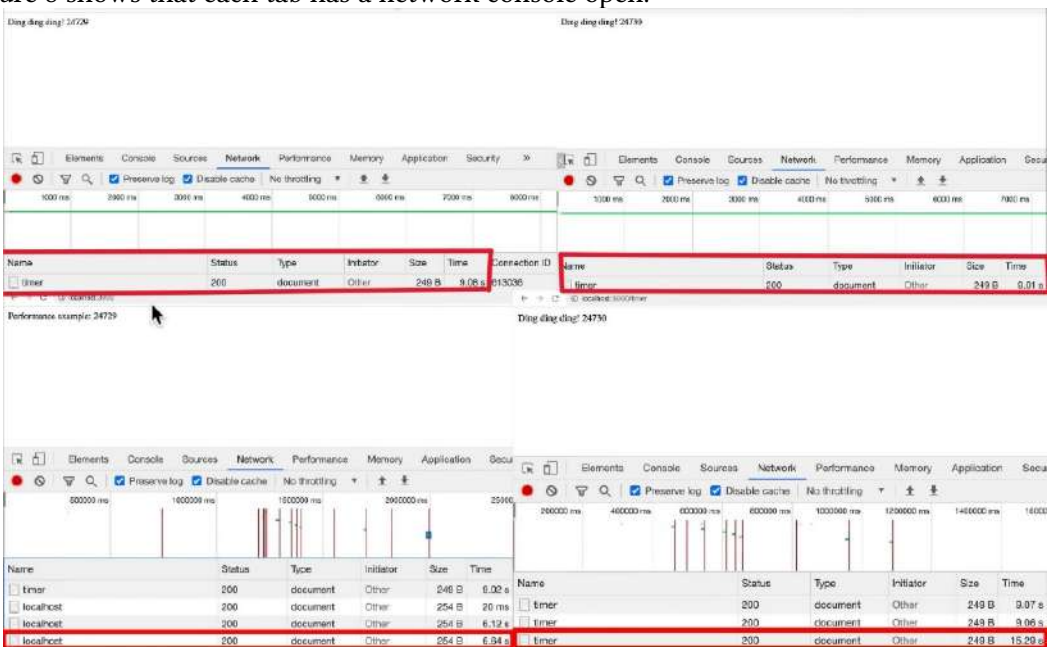

Figure 8: Experiment, temporary cluster shortcoming

In Figure 9, we see that a total of eight requests were made.

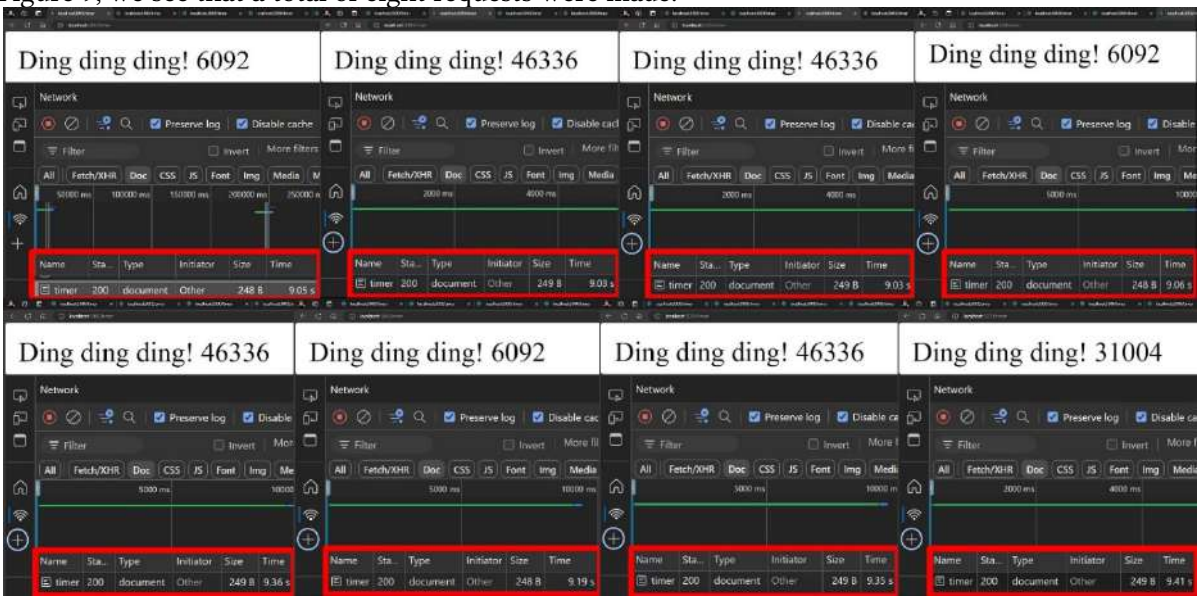

Figure 9: Parallel processing of 8 tabs simultaneously in 9 seconds

3.4.7. Key Improvements in the Revised Sections

Clear Problem Specification:

- Each section begins with a concise definition of the problem it addresses.
- Quantitative metrics (e.g., response times, CPU utilization) highlight the issue.

Structured Solution Proposal:

- The authors describe the proposed solution in a logically and technically manner.

- The authors clearly outline the implementation steps.

Measurable Results:

- The authors provide quantitative results (e.g., response times, number of simultaneous requests) to demonstrate the solution's effectiveness of the solution.
- The authors discuss the implications of the results.

Visual Aids:

- The discussion references figures (e.g., Figure 5, Figure 9) to support key points.
- Adding diagrams or tables could enhance the presentation of the results.

Metric	Before Clustering	After Clustering	Improvement
Response Time (High Load)	6.5 seconds	4 seconds	47.8% reduction
Simultaneous Requests	2	8	4x increase
CPU Utilization	25% (1 core)	100% (4 cores)	4x improvement

3.5. Load balancing

Round robin is one of the strategies used for load-balancing, a critical topic in backend development. Load-balancing refers to the distribution of tasks across a set of resources, such as dividing incoming requests among different processes. In cases where a server operates with a cluster of worker processes, a load balancer determines how to distribute requests among these processes. Figure 10 demonstrates that a load balancer receives requests from users and distributes them in a manner that evenly allocates the responsibility for handling those requests across multiple processes or potentially different applications or servers [21]. For instance, two servers running on separate machines, each hosting a set of processes capable of handling requests, can be an example of load-balancing. Requests are balanced across multiple servers and among the processes within those servers. Load-balancing is particularly effective when multiple servers or processes operate in parallel, each handling the same type of request.

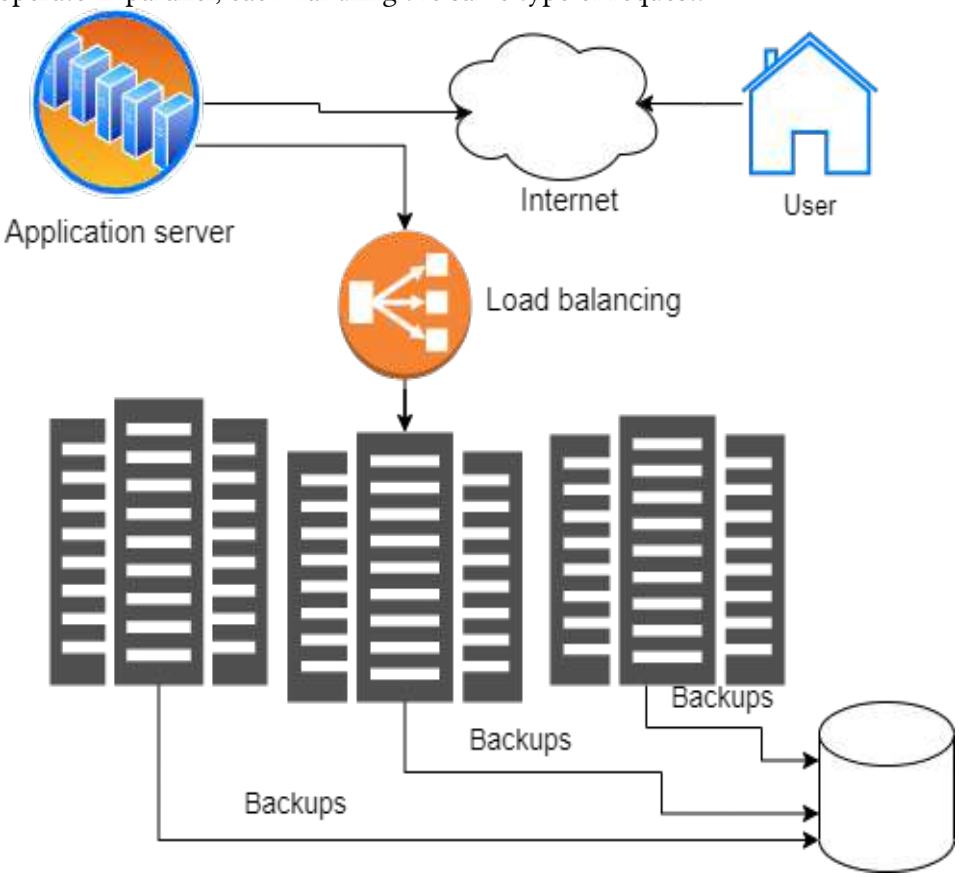

Figure 10: Load-balanced infrastructure for MediaWiki

As shown in the example, load-balancing is often discussed in the context of horizontal scaling. Horizontal scaling involves increasing an application's capacity by adding more servers or processes, while vertical scaling enhances a single-node process (e.g., upgrading the CPU for higher speed). Horizontal scaling does not require a server to be exceptionally fast or large; instead, it focuses on increasing the system's ability to handle more requests by adding additional servers or node processes, such as in a cluster [22].

Horizontal scaling and load-balancing are fundamental strategies for distributing requests in such systems. In scenarios where no prior information exists about the execution time of requests–common when handling diverse types of requests with varying execution times–two primary approaches to load-balancing are employed. One is the round-robin method, which randomly assigns incoming requests to available processes [23].

This approach, based on simple algorithms to determine which process handles a request, proves effective when precise information about execution time is unavailable.

To summarize, the cluster module in Node.js enables load-balancing for requests directed to Node's file transfer protocol (FTP) servers. This module uses a round-robin strategy to determine which process will handle incoming requests. To summarize, in Node.js, we can use the cluster module to load balance requests to our Node.js file transfer protocol (FTP) servers.

Conclusion

The chosen technology stack, which includes Node.js, MongoDB, and a clustering method, achieved an impressive 20 milliseconds of web application loading speed. Testing of multi-threaded site loading showed that simultaneous loading of two sites takes only 9 seconds, which is a significant improvement compared to the 55% additional time required for sequential loading. The clustering method allows for efficient use of users' device computing power, eliminating the need to rent servers for campaigns.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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Autonomous Identification of Distinctive Landmarks from Earth Surface Images

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Abstract

This article addresses the problem of identifying unique objects in aerial images of urban areas on the Earth's surface, which can serve as stable landmarks for UAV navigation without GPS signals. The main contribution lies in proposing an approach to transforming the image into an object-oriented vector representation (embedding) that retains structural information about those objects. The proposed approach automatically identifies the most distinctive objects, which can serve as navigation landmarks. The study focuses on urban and suburban landscapes, where buildings are chosen as landmarks and YOLOv11 is used as the deep learning model. By employing dimensionality reduction methods, in particular PCA and t-SNE, it is demonstrated that in the proposed embedding space, buildings with atypical structural or visual characteristics differ significantly from other buildings and are easily classified as outliers, making them natural landmarks for navigation. Experimental results confirm the effectiveness and potential of the proposed approach for ensuring stable UAV navigation in scenarios where GPS may be inaccessible—the accuracy of identifying buildings designated as landmarks is twice that of ordinary buildings (Recall@1 = 0.51 vs. 0.28).

Keywords

Instance embeddings, Landmark selection, Convolutional Neural Networks, UAV navigation, Satellite images, GPS-denied environments.

1. Introduction

Unmanned Aerial Vehicles (UAVs) increasingly operate in environments where GPS signals are unreliable or absent [1]. Under such conditions, visual landmarks identified from onboard camera images become the sole method for determining UAV location [2]. For accurate localisation, landmarks must be distinctive and visually recognisable under various conditions of illumination, altitude, and imaging type (e.g., UAV camera versus satellite imagery). Thus, using a set of landmarks for a given area, a route can be planned to a specified point, allowing UAV navigation without GPS signals, relying solely on environmental image analysis.

Depending on terrain characteristics, various types of objects can serve as landmarks. Given their critical practical relevance for tasks like search-and-rescue operations, deliveries, and path planning for long-range strike UAVs through densely populated urban areas, this study focuses on urban and suburban environments. Buildings, frequently prominent in these areas, have thus been chosen as potential landmarks in this research.

In recent years, deep neural networks have become widely used to obtain vector representations of features, such as embeddings. In computer vision tasks, embeddings of images or their fragments can be extracted from the hidden layers of pre-trained neural networks (such as convolutional networks or transformers), transforming visual data into compact, information-rich vectors while preserving meaningful similarity between inputs [3], [4]. Essentially, a neural network "encodes" an image into a point in latent space, placing images with similar content close together and enabling comparison using distance functions. Moreover, networks can be fine-tuned to produce embeddings with enhanced properties [5], such as invariance to common disturbances (changes in lighting, angles, etc.), thus improving their robustness in dynamic environments. Instead of raw pixel processing, UAV navigation systems can reliably recognise relevant objects using embeddings and distance metrics.

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Therefore, this research contributes to developing an approach to generate semantically rich vector representations of objects (buildings) based on their representations in the hidden layers of a convolutional neural network when processing satellite and UAV images. It doesn't require any additional training and thus can be directly applied to any segmentation CNN and other types of objects.

The proposed approach is practically significant, as it addresses the automatic identification of stable landmarks among numerous similar objects. For example, many urban buildings share architectural features, materials, or colour schemes, reducing their distinctiveness for reliable visual identification.

The structure of this paper is as follows: the *Literature Review* section surveys previous research on UAV visual localisation, including marker-based approaches, semantic dictionaries, and feature aggregation methods. The *Materials and Methods* section introduces the proposed model for extracting embeddings and automatically identifying landmark buildings. The *Results and Discussion* section presents experimental outcomes using the VPAIR dataset, their analysis, and potential improvements to the approach.

2. Literature review

Below, related research directions are reviewed.

One closely related approach is marker-based localisation, where artificial markers ensure uniqueness. For instance, YoloTag [6] employs a YOLO-based detector for fiducial markers, enabling position estimation through geometric algorithms (e.g., EPnP [7]). Although effective in indoor or restricted outdoor environments, it depends on physical marker placement, limiting scalability. Marker optimisation methods [8] face similar scalability challenges.

Semantic mapping and object dictionaries maintain recognised object annotations with geometric or class characteristics. For example, [9] combines detection with depth data (RGB-D cameras) to create semantic maps (doors, fire extinguishers, etc.). While conceptually similar, these solutions typically do not produce vector embeddings that differentiate objects within the same class, limiting the identification of distinctive landmarks. Additionally, dictionary-based approaches usually cover small-to-medium indoor areas, where objects appear repeatedly from various viewpoints within one route.

Local CNN-descriptor aggregation into global vectors has been investigated in object retrieval contexts (e.g., SPoC, CroW, R-MAC, NetVLAD [10], [11], [12], [13]), usually tested on datasets for ground-level place recognition. Despite conceptual similarities, these methods rarely perform precise object segmentation, particularly from aerial imagery. Furthermore, these methods typically produce a global vector representation for entire images, not considering individual object vector representations.

Domain adaptation methods such as CLDA-YOLO [14] address environmental variations (weather, lighting, etc.) in object detection tasks. These methods could enhance embedding robustness within the developed algorithm.

Comprehensive surveys of UAV navigation under GPS-denied conditions [15] emphasise the importance of tracking visual reference points. Yet, systems like SLAM primarily track key surface points without treating objects holistically as unique landmarks.

Literature analysis indicates limited attention to landmark-based UAV localisation methods. Most existing approaches generate descriptor vectors for entire UAV images, matching them against annotated databases. However, these descriptors may be sensitive to changes in imaging conditions and background noise.

Thus, this research aims to improve UAV localisation accuracy using stable landmarks derived from the hidden layers of a convolutional neural network when processing satellite images. These landmarks, based exclusively on unique objects, offer robustness to image noise. To achieve this goal, the following research tasks were formulated.

1. Develop a method for obtaining embeddings (vector representations) of buildings from convolutional neural network hidden layers, capable of preserving their visual and structural characteristics.
2. Create an automatic method for selecting landmark buildings based on embedding space analysis (e.g., via outlier detection).

3. Experimentally validate the proposed approach for accurately identifying buildings designated as landmarks (based on prior analysis of satellite images) on UAV images.

3. Materials and methods

3.1. Process model

For the problem under consideration, the input data consists of a set of satellite images, denoted by $I=\{I_1, I_2, \ldots, I_N\}$, covering a specific geographic area, and a fixed set of landmark object types, defined as $LandmarkTypes=\{Type_1, Type_2, \ldots, Type_t\}$ potentially comprising multiple object categories. Each satellite image I_n may contain several objects from the set $LandmarkTypes$, represented as $\{O_n^1, O_n^2, \ldots, O_n^{K_n}\}$. O – designates the set of all objects from all images I.

The proposed approach employs convolutional neural networks (CNNS) specialised for image segmentation tasks. These CNNs are trained to recognise object types from the $LandmarkTypes$ set. The output of this network for each recognized object O_n^k is the corresponding segmentation mask M_n^k.

For each object O_n^k, it is necessary to apply a mapping function f to a d-dimensional real-valued embedding vector space R^d:

$$f\left(I_n, M_n^k\right)=e_n^k, e_n^k \in R^d \tag{1}$$

The obtained vector representation of an object should possess the following properties:

- *uniqueness* – e_n^k must emphasise distinctive visual features of object O_n^k, enabling reliable differentiation from others. Let us denote by S the set of visually similar objects to O_n^k, and by D the set of visually distinct objects. The following inequality must hold:

$$\forall e^+ \in S, \forall e^- \in D: d\left(e_n^k, e^+\right) < d\left(e_n^k, e^-\right) \tag{2}$$

where $d(\cdot, \cdot)$ is a chosen distance metric (e.g., Euclidean distance).

- *robustness* – under minor transformations of the object, such as changes in viewpoint, lighting conditions, or partial occlusions, the vector representation e_n^k remains practically unchanged.

Suppose T is a transformation modelling changes in imaging conditions, and $e\left(T\left(O_n^k\right)\right)$ is the object embedding after applying transformation T. Stability is ensured if:

$$\left\| e\left(T\left(O_n^k\right)\right) - e_n^k \right\| < \epsilon, \tag{3}$$

where ϵ is a small constant defining the permissible deviation level, and $\|.\|$ denotes a vector norm (for instance, Euclidean).

After obtaining all embeddings e_n^k within the dataset, the task arises to automatically identify instances that stand out significantly in the embedding vector space. Formally, let $\{e_1, e_2, \ldots, e_M\}$ denote all object embeddings. A criterion based on outlier detection algorithms is introduced, distinguishing objects with distinctive features from those forming dense clusters. Objects thus identified are labelled as landmarks. The set L of such landmark objects represents the final output of the landmark detection task.

These landmark objects, identified through the described method, form the basis for UAV route planning. In scenarios lacking GPS signals, a UAV can determine its location by recognising selected stable and unique landmarks on the terrain.

3.2. Hypothesis

An object database along the flight trajectory is prepared before the mission to facilitate UAV navigation based on visual features. These objects are extracted from satellite images, each associated with geolocation markers. During flight, the UAV identifies objects from onboard camera images and searches for matching objects in this pre-formed database. Upon finding a match, the UAV uses the object's geolocation marker to determine its current position.

Generally, it is reasonable to assume that if an object identified in a satellite image acts as a landmark, standing out from surrounding objects due to unique features, this distinction will persist in images captured by UAV cameras. Based on these assumptions, the core hypothesis can be articulated as follows: if a mapping into vector space preserving semantic and structural features is applied to the set of objects in an image, landmark objects will distinctly differ from other objects in the embedding space, regardless of whether they originate from UAV camera images or satellite imagery. Consequently, when receiving images from onboard cameras, the UAV can significantly more accurately identify precisely those objects recognised as landmarks by the approach proposed in this study.

Thus, the essence of the proposed method lies in the specific utilisation of convolutional neural networks to create an embedding vector space that preserves semantic and structural characteristics. It is well-known that convolutional neural networks learn hierarchical feature representations, with initial layers capturing local textures and edges, and deeper layers encoding higher-level forms or semantic features. An embedding with hierarchical features of the specific object is effectively obtained by constructing a vector from activations corresponding to a particular object from various hidden layers.

3.3. Method steps

The main steps of the proposed approach are illustrated in Fig. 1.

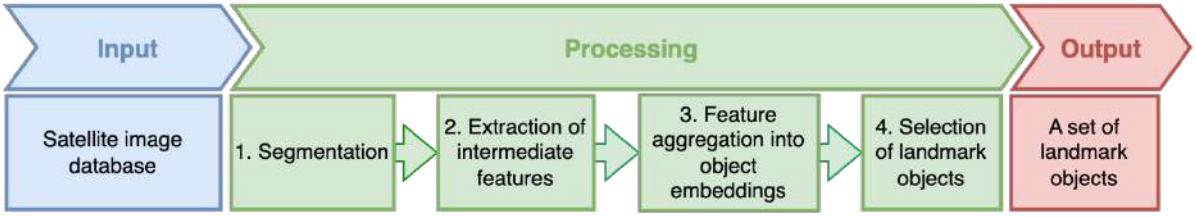


Figure 1: The main steps of the proposed approach

The input information of the approach (Fig. 1) consists of a set of satellite images of a specific territory I and a fixed set of object types that potentially serve as landmarks, referred to as $LandmarkTypes$.

In the first step of the proposed approach, the set O of potential landmark objects is formed by segmenting images from the satellite imagery database. A CNN-based segmentation model, trained to recognise objects from the $LandmarkTypes$ set, is applied to each image I_n, resulting in $\{M_n^k\}$ – a set of masks and corresponding confidence scores. Only objects with a confidence coefficient above a threshold θ are selected for reliability.

In step 2, intermediate features of objects are extracted from the hidden layers of the convolutional neural network. To describe this process, denote the feature map of a CNN at layer $\boldsymbol{I}$ as $\boldsymbol{F_l} \in R^{C_l \times H_l \times W_l}$, where C_l is the number of channels at layer $\boldsymbol{I}$, and $H_l ma W_l$ represent the height and width, in pixels, of the feature maps at layer $\boldsymbol{I}$, respectively. Let $l_1, l_2, \ldots, l_L$ be parameters corresponding to the backbone CNN layers used for embedding formation. During segmentation in step 1, feature maps F_l are extracted from the backbone CNN layers $l_1, l_2, \ldots, l_L$. Each layer l is associated with a stride ρ_l, defining the reduction in spatial resolution of feature maps compared to the original image. Accordingly, each mask M_n^k is resized to dimensions $\widetilde{M}_n^{kl}$ based on the corresponding stride ρ_l of the feature map F_l. This alignment ensures pixels in the mask correspond precisely to positions on the feature map, thus isolating only the area corresponding to the detected object O_n^{kl}.

Step 3 involves aggregating intermediate features to form the final object embeddings. Since each object may vary in size, occupying different-sized regions on the activation maps, an aggregation function must be employed to obtain a fixed-dimensional vector. Generally, the aggregation function can be a parameterised function trainable via backpropagation, such as a graph neural network [16].

For each layer l and object k, the aggregation is computed as:

$$z_c^l = \mathrm{agg}\left(\left\{F_l[c,u,v] \middle| (u,v) \in \widetilde{M}_n^{kl}\right\}\right) \quad (4)$$

where the aggregation function can be, for example, max pooling or average pooling.

Max pooling:

$$z_c^l = \max_{(u,v)\in\widetilde{M}_n^{kl}} F_l[c,u,v] \quad (5)$$

Average pooling:

$$z_c^l = \frac{1}{\left|\widetilde{M}_n^{kl}\right|} \sum_{(u,v)\in\widetilde{M}_n^{kl}} F_l[c,u,v] \quad (6)$$

Values z_c^l, computed for all C_l channels across selected convolutional layers $l_1, l_2, \ldots, l_L$, are concatenated to form the final embedding $e_n^k \in R^d$:

$$e_n^k = \left[z_c^l \middle| c \in 1..C_l, l \in l_1, l_2, \ldots, l_L\right] \quad (7)$$

Thus, the embedding dimension d is determined by the total number of channels in convolutional layers $l_1, l_2, \ldots, l_L$, where each dimension effectively represents the presence of patterns detected by corresponding convolutional filters:

$$d = \sum_{l \in l_1, l_2, \ldots, l_L} C_l \quad (8)$$

Step 4 identifies landmark objects. Initially, all embeddings $\{e_1^1, e_1^2, \ldots\}$ are combined into the set E. Since each embedding dimension corresponds to a specific convolutional filter trained to recognize particular image structures, embeddings implicitly represent visual features of objects. Based on the initial assumption, objects with atypical visual characteristics yield embeddings with atypical values. Consequently, the final stage entails differentiating "typical" points in the embedding space from those with rare features. Theoretically, this problem class corresponds to outlier detection methods aimed at identifying objects statistically deviating from the majority.

Generally, the outlier detection task can be formulated as follows: let $E = \{e_1, e_2, \ldots, e_M\} \subset R^d$, where each vector e_i is an object embedding. Suppose that for most points, the feature distribution approximates a “typical” (“normal”) subset E_{norm}, while a few points $e_j \in E_{\text{out}}$ significantly deviate from this distribution. Formally, an evaluation function is assumed:

$$s: R^d \to R, \quad (9)$$

which returns the deviation from the typical distribution for each e_i. If $s(e_i)$ exceeds a threshold s_{thr}, e_i is considered an outlier (anomaly). In our context, objects with such embeddings possess distinctive visual characteristics and can serve as stable landmarks. Hence, applying an outlier detection algorithm to set E forms the final landmark object set $L = \{e_i \vee s(e_i) > s_{thr}\}$.

The landmark object set L is the output of the proposed approach.

3.4. Evaluation metrics

The UAV localisation problem considered in this study is classically framed as a retrieval task. Consequently, literature conventionally evaluates UAV localisation methods using the Recall@N metric [17], [18]. This metric considers a retrieval result as a true-positive for a given query if the corresponding image from the database appears among the top N retrieved images:

$$\text{Recall@N} = \frac{M_Q}{N_Q}, \quad (10)$$

where N_Q is the total number of query images, and M_Q is the number of queries with at least one correct match within the top-N results.

This metric is popular within computer vision communities and suits applications employing post-processing to eliminate false-positive matches.

4. Results and discussion

4.1. Dataset

The VPAIR dataset [19] was selected for conducting experiments – a dataset designed explicitly for evaluating visual place recognition tasks and UAV localisation based on images from onboard cameras. Data collection occurred on October 13, 2020, during a flight of a light aircraft at altitudes ranging from 300 to 400 meters above ground, covering an area between Bonn, Germany, and the Eifel Mountain range, with a total route length of 107 km. The dataset includes imagery captured perpendicular to the Earth's surface and high-precision pose/orientation data obtained using GNSS/INS systems. The VPAIR dataset contains 2,788 aerial photographs paired with corresponding satellite images and *does not* provide any annotations about the objects in the images. The satellite images were gathered from Geobasis NRW, a state-funded geodata repository under a permissive open data license. It provides comprehensive coverage of the entire state of Nordrhein-Westfalen, Germany. During image capture, the aircraft maintained a speed of 150 km/h and a frame rate of 1 Hz, resulting in approximately 41.7 meters between consecutive image centres.

Figure 2: Examples of images from the VPAIR dataset. Left – aerial images captured from aircraft; right – corresponding satellite images

4.2. Experiment description

The YOLOv11 segmentation convolutional neural network [20], pre-trained for building segmentation in satellite images, was utilised in the experiments. It is important to emphasise that the proposed method *uses the pre-trained CNN* that segments the objects of interest and *requires no additional training* on the target dataset.

For outlier detection – specifically to identify landmark objects – Isolation Forest [21], a tree-based algorithm, was chosen. The selection of this algorithm was motivated by three main reasons: tree-based algorithms are robust against variations in feature value ranges and thus do not require normalisation; they operate rapidly; and they only need two primary parameters that are easily adjustable (the proportion of objects considered as outliers and the number of trees). This straightforward algorithm facilitated focusing on hypothesis verification and proved sufficient to confirm it. Subsequent experiments present results obtained with Isolation Forest configured with 500 trees and 1% outliers.

To validate the proposed hypothesis, the following sub-hypotheses must be tested:

1) The proposed embedding generation approach encodes structural and semantic information about objects.
2) The accuracy of landmark building retrieval from UAV images is significantly higher than that of typical (non-landmark) buildings.

It should be noted that the VPAIR dataset contains no specific annotations for buildings; thus, the set of buildings used in this study was obtained using the YOLOv11 segmentation model.

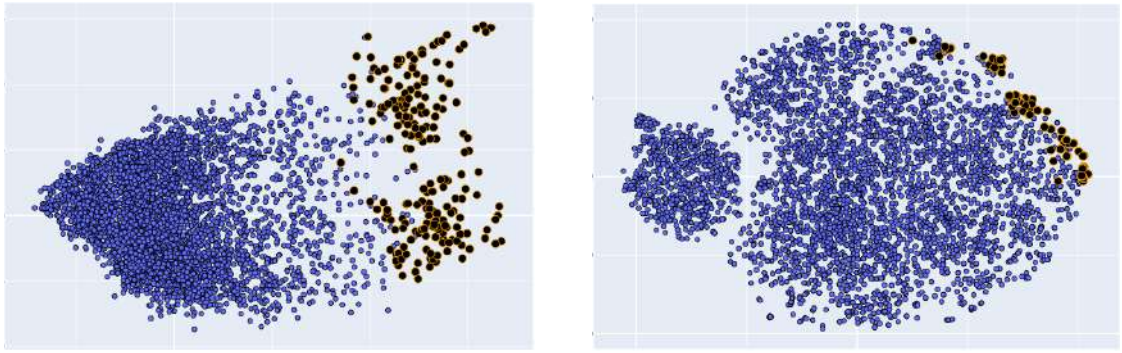
The absence of building ground-truth annotations in the dataset makes it impossible to quantify misclassifications, false positives, and false negatives in the object detection process on the VPAIR dataset.

However, for the *pre-trained* YOLOv11 used in the experiments, the following metrics are reported by its developers: 18,794 true positives, 8,462 false positives, and 5,628 false negatives. At the same time, true-negative background pixels are undefined for segmentation. Across seven random splits the model attained mAP 0.754, precision 0.771, recall 0.680 and F1 0.722. The reported values establish a realistic error bound when the model is applied to the VPAIR dataset, and the manual inspection of the predictions confirms its high performance and generalisation to this dataset.

To verify the first hypothesis, visualisation of the building embeddings—obtained from segmented satellite images—was conducted using two dimensionality reduction methods: PCA for analysing linear dependencies and t-SNE for non-linear dependencies. Researchers then visually inspected the proposed method and provided qualitative assessments.

Validation of the second hypothesis required manual data labelling to create a benchmark set, as the VPAIR dataset contains no building annotations. Given corresponding satellite and UAV images and buildings previously segmented by YOLOv11, matching identical buildings across UAV and satellite images was necessary. Considering the time-intensive nature of manual labelling, a random, non-repetitive sample of 100 landmark buildings and 100 typical buildings was selected for annotation. For the embeddings of each of the selected 200 UAV buildings, the five nearest embeddings from satellite images were identified using the L2 norm. The metrics Recall@1 and Recall@5 were calculated separately for landmark and typical buildings.

4.3. Analysis of the obtained embedding space



a) b)

Figure 3: Visualisation plots of building embeddings from satellite images using dimensionality reduction methods: left a) – PCA; right b) – t-SNE. Black points represent landmark buildings, and blue points represent typical buildings.

Visualisation results of building embeddings obtained via dimensionality reduction methods (Fig. 3) demonstrate that the embedding space is structured.

The PCA plot shows that most buildings concentrate on the left side, with the remaining points forming an elongated, sparse tail. It is logical to hypothesise that the dense concentration corresponds to numerous typical buildings, while the progressively extending tail represents buildings with increasing visual uniqueness. Visual inspection of points in these areas (Fig. 4) confirms this assumption (Fig.5 and Fig.6). Thus, the selection of buildings at the tail end of this distribution by the outlier detection algorithm as landmarks aligns with expectations, as these points correspond to the most distinctive structures.

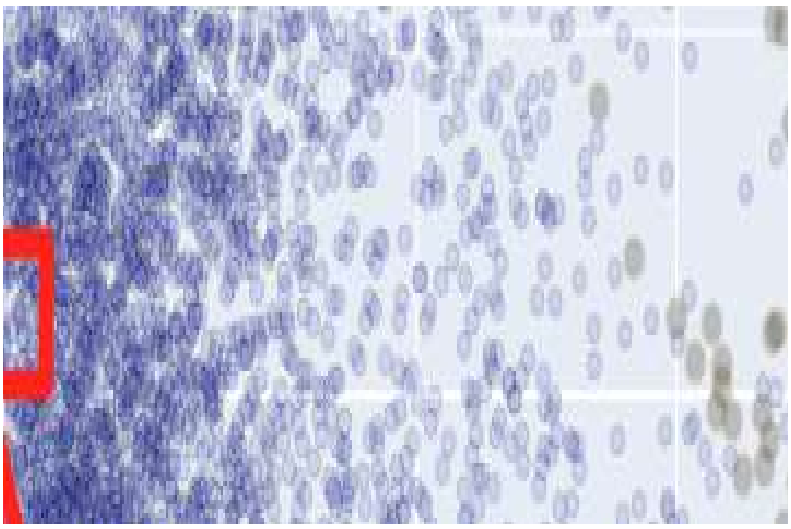


Figure 4: Visualisation plot of building embeddings from satellite images using PCA dimensionality reduction. Segment a) highlights a region with a high density of points corresponding to typical small buildings (Fig. 5), while segment b) represents a cluster of landmark buildings (Fig. 6)

Figure 5: Examples of typical small buildings, outlined with red rectangles, corresponding to selected points in Fig. 4a.

Figure 6: Examples of landmark buildings, outlined with red rectangles, corresponding to points from the highlighted cluster in Fig. 4b.

The t-SNE visualisation, which reveals non-linear relationships, displays multiple small clusters grouping visually similar buildings or identical buildings from adjacent frames. The fact that landmark buildings cluster at the edges of the point cloud, rather than being dispersed throughout, indicates good embedding space structure. A particularly notable cluster emerges distinctly in the left region of the t-SNE plot. Visual inspection revealed that this cluster corresponds to small buildings with typical structures positioned at image boundaries (so buildings partially extend beyond the frame edge). Examples of these buildings and their corresponding points in the t-SNE visualisation are illustrated in Fig.7-9.

Thus, the proposed method effectively distinguishes landmark buildings from typical ones within the embedding space. Selected landmark buildings exhibit unique characteristics, often large or irregular shapes. Visually similar buildings in size, colour, and form have close embeddings. The neighbourhoods around embeddings situated in regions of greater uniqueness mostly contain embeddings of the same buildings from adjacent frames, indicating stability of the vector representation across different viewpoints. However, as uniqueness decreases, the neighbourhoods increasingly include buildings that, although visually similar, originate from spatially distant locations.

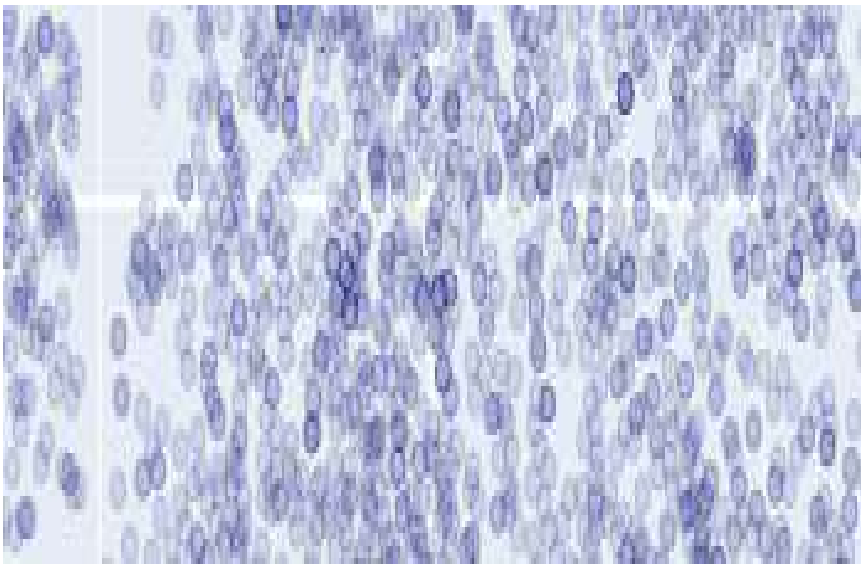


Figure 7: Visualisation plot of building embeddings from satellite images using t-SNE dimensionality reduction. On the segment a) – a region with a high density of points corresponding to typical small buildings is highlighted (Fig. 8); on the segment b) – a cluster of landmark buildings is selected.

Figure 8: Examples of typical small buildings, outlined with red rectangles, corresponding to selected points in Fig. 7a. These buildings have the distinctive characteristic of being located at the image boundaries, partially extending beyond the image frame

Figure 9: Examples of landmark buildings, outlined with red rectangles, corresponding to points from the highlighted cluster in Fig. 7b.

4.4. Comparison of retrieval accuracy for typical and landmark buildings

The quantitative measurements presented in Table 1 demonstrate that the accuracy of UAV-based searches for landmark buildings nearly doubles compared to searches for typical buildings, thus confirming the efficacy of the proposed approach. The Recall@5 value indicates that incorporating a post-filtering stage for the top-5 most similar buildings could potentially increase the current implementation's Recall@1 up to 0.66.

Several special cases were observed during the evaluation phase. For example, YOLOv11 may detect the same building twice at the building segmentation stage from images. Still, in one instance, YOLO might merge the building with an adjacent one, as illustrated in cases a) and b) in Figure 10. However, the proposed approach effectively generates embeddings that robustly encode semantic and structural information, rendering these representations resilient to CNN segmentation errors; in both cases, the correct matching building was identified successfully.

Table 1
Metrics for the retrieval of typical buildings and landmark buildings

Metric		Recall@K	
		K=1	K=5
Buildings	Landmark	**0.51**	**0.66**
	Typical	0.28	0.46

While cases a) and b) focused on searches of landmark buildings, case c) involved a building classified as typical, characterised by medium size and a visually distinct angular shape. Despite the corresponding satellite image building being rotated by more than 90°, it was accurately identified as the top-1 match, demonstrating the embeddings' robustness to object rotations. Case d) involved a typical building—a long residential structure with an orange roof. Such buildings are numerous in the dataset, and semantically retrieved buildings were correct, matching the elongated rectangular shape and roof colour. However, none matched the UAV-captured building, emphasising the importance of selecting truly unique buildings for search accuracy.

Figure 10: Examples demonstrating the performance of the proposed approach in edge cases. The first row shows the UAV-captured building for which a match is searched from the satellite-based building database. The second row presents the corresponding satellite-based reference building. The subsequent rows illustrate the most similar buildings based on L2 distance embeddings. For compactness, we show only the top-2 most similar samples. In cases a) and b), the same landmark building was segmented twice by YOLOv11—case a) shows correct segmentation, while case b) merges the building with an adjacent one into a single segment. Despite this segmentation discrepancy, the correct corresponding satellite building was successfully identified within the top 5

in both cases, demonstrating the robustness of embeddings against CNN segmentation errors. Case c) involves a uniquely shaped yet classified as a typical building that was rotated more than 90° in the satellite imagery. Despite this rotation, the correct corresponding building was identified as the top-1 match, indicating robustness of embeddings to object rotations. In case d), a typical elongated residential building with an orange roof is considered. Although the retrieved buildings are semantically correct, being elongated rectangles with similar roof colours, none precisely match the UAV-based query building. This emphasises the importance of selecting unique landmark buildings to ensure retrieval accuracy.

4.5. Limitations

The experimental validation in this study was conducted within an urban environment, using buildings as landmarks. Both satellite and UAV images were captured during daylight from the same vertical, top-down perspective.

Significantly, the specific set of landmark objects for a given set of satellite images depends on the convolutional neural network used. Different neural networks might segment the same image differently, potentially failing to identify buildings or merging multiple adjacent buildings into a single segment. Additionally, object embeddings generated by these networks may differ, resulting in variations in the final landmark object set.

The calculation of Recall@1 and Recall@5 metrics for matching accuracy between UAV and satellite images required human labelling of search results. Due to the time-intensive nature of this task, the test dataset size was limited to 200 unique buildings.

4.6. Future work

Future directions for improvement include extending this approach to other types of urban landmarks (e.g., intersections, roads, sports fields) and different environments (e.g., forests, fields).

An interesting research aspect involves the impact of aggregation functions on the embedding space and the objects forming the final landmark set. Combining graph neural networks, trainable via backpropagation, with Contrastive Learning methods [22] could enhance the invariance of object embeddings to variations in viewing angles or lighting conditions.

To create landmark sets without the strict requirement for a fixed number (as seen in Isolation Forest), and considering additional practical constraints, future improvements may involve more flexible outlier detection algorithms. An alternative approach could replace outlier detection with clustering algorithms that do not require a fixed cluster count. Here, landmarks could be represented by objects in tiny clusters or those lying outside of any cluster, with the introduction of supplementary constraints, such as a maximum allowable distance between neighbouring landmarks.

5. Conclusions

This work proposes an approach for identifying unique landmark objects by analysing embeddings obtained from convolutional neural networks. The study aims to enhance UAV localisation by isolating distinctive landmark buildings within an embedding space encoding structural and visual features.

Experimental results successfully met this goal, revealing landmark building identification accuracy nearly twice as high as typical building recognition (Recall@1 = 0.51 and Recall@5 = 0.66 versus 0.28 and 0.46, respectively).

Nevertheless, the current implementation has limitations, notably its application to navigation within urban and suburban environments under good lighting conditions, and dependency on a particular segmentation model.

Future work aims to broaden this approach to various object and terrain types and investigate more adaptable feature aggregation and anomaly detection methods. Such enhancements could expand the system's applicability and navigational accuracy. Ultimately, refining this approach could enable fully automated UAV route planning based on visual features in GPS-denied environments. The only parameters needed would include satellite surface imagery, specific landmark set constraints derived from UAV technical specifications, the selected convolutional neural network deployed on the UAV, and defined start and end route points.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Capturing Bitcoin Market Dynamics: Assessing Advanced Permutation Entropy Metrics as Early-Warning Indicators

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Abstract

Permutation entropy (PEn) is a widely adopted nonlinear statistical measure for quantifying complexity in time series data. Despite its conceptual clarity and computational efficiency, classical PEn has notable limitations, particularly its disregard for amplitude variations in time series data and the simplistic handling of sequences containing equal-valued observations. Although modified PEn methods exist, their potential as early-warning indicators for cryptocurrency market crashes remains largely unexplored. This paper addresses these limitations by conducting a comparative analysis of classical PEn and three enhanced methods: weighted permutation entropy (WPEn), amplitude-aware permutation entropy (AAPEn), and uniform quantization-based permutation entropy (UPEn). Specifically, these entropy metrics are employed to analyze the Bitcoin market crash from December 2017 to February 2018, utilizing a sliding window approach. Empirical results demonstrate that amplitude-enhanced entropy methods effectively capture nuanced market dynamics and fluctuations, offering more precise and more reliable signals of impending market instability. This study confirms the value of advanced entropy measures in cryptocurrency markets and underscores their potential as robust indicators for detecting and forecasting financial crashes.

Keywords

permutation entropy, weighted permutation entropy, amplitude-aware permutation entropy, uniform quantization-based permutation entropy, complexity measures, cryptocurrency market crash, Bitcoin, early warning indicators, market instability

1. Introduction

Quantifying the complexity inherent in temporal data offers profound insights into the underlying dynamics of complex systems, such as cryptocurrency markets [1, 2]. Despite its significance, complexity lacks a universally accepted definition [3, 4]. Among various methods proposed, entropy-based metrics have emerged as particularly effective in assessing complexity, given their conceptual clarity and computational efficiency [5]. Entropy encapsulates complexity by measuring the degree of randomness or unpredictability in time series data. These entropy methods can be applied across diverse types of data, including deterministic, chaotic, stochastic, stationary, and nonstationary processes [6].

Cryptocurrency markets, especially Bitcoin, exhibit pronounced volatility, high noise levels, and nonlinearity, making classical linear analytical techniques insufficient for comprehensive market analysis [7, 8]. Entropy-based approaches provide a viable alternative to traditional methods such as fractal dimension [9], Lyapunov exponent [10], or Lempel-Ziv complexity [11], particularly due to their robustness when dealing with short, noisy, and nonstationary data. Previous research has successfully demonstrated the efficacy of information-theoretic entropy measures in analyzing complex financial time series [12, 13, 14].

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The efficient market hypothesis (EMH), initially formulated by Fama [15], postulates that market prices rapidly incorporate all available information, leading to random walk-like behavior in asset price fluctuations. Under EMH conditions, informational efficiency implies maximum entropy states, where no predictable profit opportunities remain due to information symmetry among market participants. However, empirical observations suggest real-world cryptocurrency markets exhibit varying degrees of efficiency, with entropy levels fluctuating over time due to market sentiment, regulatory news, technological developments, or speculative trading activities [16]. Entropy metrics thus provide intuitive and practical tools for capturing shifts in market efficiency regimes, highlighting their utility in detecting impending market disruptions.

Cryptocurrency market crashes, particularly in Bitcoin, are characterized by complex, nonlinear interactions and rapid transitions from relatively stable states towards chaotic regimes [17, 18, 19]. Understanding these crashes demands a nuanced examination of their emergent properties, including increased correlation among market participants, evolving self-organized patterns, and heightened systemic risk. Permutation entropy (PEn), a powerful nonlinear complexity metric, and its various modified forms are promising tools to investigate these dynamics.

This study focuses specifically on the Bitcoin market crash occurring between December 2017 and February 2018 [2], a significant event marked by the bursting of a speculative bubble. Using classical permutation entropy and several enhancements thereof, we employ a sliding time-window methodology to observe temporal changes in complexity. This approach reveals patterns and trends indicative of impending market crises. The identification of early-warning signals based on permutation entropy measures provides substantial benefits not only to traders and investors but also to policymakers and regulatory authorities. Recognizing precursor signals of market crashes enables stakeholders to implement proactive measures, mitigate systemic risks, and formulate informed short- to long-term strategies.

2. Permutation entropy methodology

2.1. Classical Permutation Entropy

Permutation entropy (PEn) is a complexity measure that quantifies the predictability of a time series by analyzing the frequency distribution of its ordinal (permutation) patterns [20]. Inspired by Claude Shannon's information entropy [21], PEn has proven effective for various real-world data analysis applications, particularly in finance and economics [22, 23].

Shannon entropy (ShEn) quantifies the uncertainty associated with a discrete random variable R having a probability distribution o(b) as follows:

$$H(X) = -\sum_{x \in \chi} p(x) \log p(x), \tag{1}$$

where χ denotes the set of possible outcomes for X. ShEn measures the number of bits needed to encode information, thus reflecting the unpredictability of outcomes. Variations of ShEn, such as Rényi entropy and joint entropy, have also been successfully employed in different fields to characterize random processes [24, 25].

PEn applies this concept to time series data by investigating ordinal patterns, thus capturing temporal dynamics and predictability. Consider a univariate time series $\left\{x_t\right\}_{t=1}^{N}$ with N data points. To identify ordinal patterns, the series is segmented into embedding vectors defined by two parameters: embedding dimension d_E (length of the subsequences) and time delay τ. For each time t, embedding vectors are constructed as follows:

$$\vec{X}_t^{d_E,\tau} = \left(x_t, x_{t+\tau}, \ldots, x_{t+(d_E-1)\tau}\right), t = 1, \ldots, N-\left(d_E-1\right)\tau. \tag{2}$$

Each embedding vector $\vec{X}_t^{d_E,\tau}$ is mapped onto one of $d_E!$ possible ordinal patterns $\left\{\pi_i\right\}_{i=1}^{d_E!}$ based on the relative ordering of its elements. Specifically, the ordinal pattern represents the permutation required to sort vector components into ascending order. For example, given a time series segment

$(5,8,4)$ with $d_E=3$ and $\tau=1$, the ordinal pattern is classified as $\pi_i=(2,0,1)$ since the order of indices corresponding to ascending values is $(3,1,2)$.

Table 1 summarizes all possible ordinal patterns for an embedding dimension of $d_E=3$:

Table 1
Possible ordinal patterns for embedding dimension $d_E=3$

Ordinal Pattern	(x_a,x_b,x_c)	Condition
π_1	$(3,2,1)$	$x_t>x_{t+\tau}>x_{t+2\tau}$
π_2	$(3,1,2)$	$x_t>x_{t+2\tau}>x_{t+\tau}$
π_3	$(2,3,1)$	$x_{t+\tau}>x_t>x_{t+2\tau}$
π_4	$(2,1,3)$	$x_{t+2\tau}>x_t>x_{t+\tau}$
π_5	$(1,3,2)$	$x_{t+\tau}>x_{t+2\tau}>x_t$
π_6	$(1,2,3)$	$x_t<x_{t+\tau}<x_{t+2\tau}$

The probability of each ordinal pattern π_i occurring in the time series is computed by

$$p(\pi_i)^{d_E,\tau}=\frac{¿\left\{\vec{X}_t^{d_E,\tau}\vee\vec{X}_t^{d_E,\tau}\ corresponds\ \text{to}\ pattern\ \pi_i\right\}}{N-(d_E-1)\tau},i=1,\ldots,d_E!. \tag{3}$$

Finally, the permutation entropy for the time series is defined as

$$PEn(X)^{d_E,\tau}=\frac{-1}{\ln d_E!}\sum_{i=1}^{d_E!}p(\pi_i)^{d_E,\tau}\ln p(\pi_i)^{d_E,\tau}, \tag{4}$$

where the normalization term $(\ln d_E!)^{-1}$ ensures that the entropy values range between 0 (completely predictable series) and 1 (completely random series), thus facilitating meaningful comparisons across different time series and applications.

2.2. Weighted Permutation Entropy

While classical permutation entropy effectively captures complexity by analyzing ordinal patterns, it disregards amplitude-related information inherent in the original time series data. This limitation can lead to several drawbacks: (i) significant amplitude differences between data points within ordinal patterns are ignored, potentially losing critical information; (ii) patterns with substantial amplitude variations and those resulting from minor fluctuations (noise) contribute equally to the permutation entropy measure, diminishing the method's sensitivity; and (iii) ignoring amplitude may reduce the discriminative power of permutation entropy when applied to real-world data, such as financial or physiological signals.

To address these limitations, Fadlallah et al. [26] introduced weighted permutation entropy (WPEn), which integrates amplitude information by assigning different weights to each ordinal pattern based on the local variance or energy of the corresponding subsequences. The main idea behind WPEn is to emphasize ordinal patterns derived from subsequences with more considerable amplitude variations, thus incorporating valuable amplitude-related information.

Formally, for each embedding vector $\vec{X}_t^{d_E,\tau}$, weight w_t is defined using the variance of the elements within the subsequence as

$$w_t=\frac{1}{d_E}\sum_{k=1}^{d_E}\left(x_{t+(k-1)\tau}-\left\langle\vec{X}_t^{d_E,\tau}\right\rangle\right)^2, \tag{5}$$

where $\left\langle\vec{X}_t^{d_E,\tau}\right\rangle$ represents the arithmetic mean of the subsequence:

$$\left\langle \vec{X}_t^{d_E,\tau} \right\rangle = \frac{1}{d_E} \sum_{k=1}^{d_E} x_{t+(k-1)\tau}. \tag{6}$$

Once the weights are computed, the weighted probability of each ordinal pattern π_i is given by

$$p_w\left(\pi_i\right)^{d_E,\tau} = \frac{\sum_{t:\vec{X}_t^{d_E,\tau} \in \pi_i} w_t}{\sum_t w_t}, i = 1, \ldots, d_E!, \tag{7}$$

where the denominator ensures normalization, preserving the probabilistic interpretation $\sum_{i=1}^{d_E!} p_w\left(\pi_i\right)^{d_E,\tau} = 1$.

The WPEn is then defined analogously to the ShEn formulation as

$$WPEn\left(X\right)^{d_E,\tau} = -\sum_{i=1}^{d_E!} p_w\left(\pi_i\right)^{d_E,\tau} \ln p_w\left(\pi_i\right)^{d_E,\tau}. \tag{8}$$

WPEn can be seen as an amplitude-sensitive adaptation of weighted Shannon entropy [27], providing a way to measure complexity when outcomes have different importance levels or intensities. Thus, WPEn significantly enhances permutation entropy's utility by effectively combining both ordinal and amplitude information, making it particularly suitable for analyzing complex signals such as those encountered in financial markets and other noisy real-world environments.

2.3. Amplitude-Aware Permutation Entropy

Although WPEn successfully incorporates amplitude variance into the entropy calculation, it still exhibits some limitations. Specifically, WPEn cannot differentiate cases where a constant offset is added to a time series since the variance remains unchanged under such transformations. Additionally, WPEn is less sensitive to scenarios involving minor amplitude shifts or additive constants, potentially limiting its effectiveness in capturing subtle but meaningful amplitude-based information within a signal.

To address these limitations, Azami and Escudero [28] introduced amplitude-aware permutation entropy (AAPEn), a refined entropy measure explicitly designed to capture amplitude information more comprehensively. This method improves upon WPEn by assigning variable contributions to ordinal patterns based on both the absolute amplitude levels and the relative changes between consecutive samples.

To illustrate the shortcomings of standard permutation entropy methods regarding amplitude information:

1. Classical permutation entropy relies solely on ordinal relationships, ignoring amplitude magnitude. For instance, sequences such as $(5,20,8)$ and $(5,12,8)$ share an identical ordinal pattern (021), despite significant amplitude differences. Similarly, sequences $(5,12,8)$ and $(25,37,30)$ also share the same ordinal pattern due to the absence of amplitude considerations.
2. In the presence of equal consecutive values, traditional ordinal analysis may yield ambiguous results. Bandt and Pompe [20] suggested resolving ties based on the order of occurrence or by adding small noise. However, this approach is problematic because, for example, the vectors $(3,9,9)$ and $(3,6,9)$ can both yield ambiguous ordinal patterns. This issue is particularly relevant in discretely sampled or digitized signals.

To mitigate these issues, AAPEn modifies the traditional histogram-based ordinal pattern encoding by introducing amplitude-based weighting. Specifically, each embedding vector contributes

a variable amount to the ordinal pattern frequency histogram instead of uniformly incrementing by one:

$$p(\pi_i)^{d_E,\tau} = p(\pi_i)^{d_E,\tau} + L\left(\vec{X}_t^{d_E,\tau}\right), if\ \vec{X}_t^{d_E,\tau}\ corresponds\ \text{to}\ pattern\ \pi_i, \tag{9}$$

where the amplitude-based adjustment coefficient $L\left(\vec{X}_t^{d_E,\tau}\right)$ is defined as

$$L\left(\vec{X}_t^{d_E,\tau}\right) = \frac{A}{d_E}\sum_{k=1}^{d_E}\left|x_{t+(k-1)\tau}\right| + \frac{1-A}{d_E-1}\sum_{k=2}^{d_E}\left|x_{t+(k-1)\tau} - x_{t+(k-2)\tau}\right|, \tag{10}$$

with $A \in [0,1]$ balancing the relative importance of amplitude magnitudes and consecutive amplitude changes.

The final amplitude-aware probabilities for each ordinal pattern are normalized as follows:

$$p(\pi_i)^{d_E,\tau} = \frac{p(\pi_i)^{d_E,\tau}}{\sum_{t=1}^{N-(d_E-1)\tau} L\left(\vec{X}_t^{d_E,\tau}\right)}. \tag{11}$$

The parameter A allows flexibility in emphasizing either mean amplitude levels or amplitude difference. For anomaly detection tasks, setting $A \ll 0.5$ emphasizes sudden amplitude changes, enhancing sensitivity. Conversely, for tasks like financial crash detection, where both mean amplitude and amplitude fluctuations carry importance, a balanced value ($A = 0.5$) is recommended.

Additionally, the choice of delay parameter τ significantly impacts AAPEn results. While a delay of $\tau = 1$ is typically adequate, certain signal characteristics, such as single-sample spikes versus extended spikes, may benefit from greater delays $(\tau > 1)$. Careful selection of τ helps avoid aliasing-like effects, preserving the integrity of amplitude and frequency characteristics within the signal. For analyses at multiple temporal scales, frameworks such as those proposed by Costa et al. [29] or Azami et al. [30] can further enhance the robustness of AAPEn.

By effectively capturing amplitude dynamics alongside ordinal structure, AAPEn provides a powerful and flexible tool, well-suited for nuanced applications such as cryptocurrency market analysis, anomaly detection, and other complex time series tasks.

2.4. Uniform Quantization-Based Permutation Entropy

Chen et al. [31] introduced uniform quantization-based permutation entropy (UPEn), a refined entropy measure designed to capture amplitude variations and mitigate ambiguities associated with equal-valued data points. Unlike classical PEn, which relies solely on ordinal patterns, UPEn incorporates amplitude information through a quantization-based encoding approach. The method involves two primary steps:

1. Pattern Formation: Embedding vectors are symbolized via uniform quantization.
2. Entropy Estimation: The entropy is calculated based on the distribution of quantized patterns.

Initially, the time series is segmented into embedding vectors $\vec{X}_t^{d_E,\tau}$. The first elements of these embedding vectors $\vec{X}_{t,1}^{d_E,\tau}$ undergo uniform quantization (UQ), transforming the continuous data into discrete symbols. For a time series X, the UQ process assigns each value to one of D quantization levels, as defined by

$$UQ(x) = \left\lfloor \frac{x - x_{min}}{\Delta} \right\rfloor, where\ \Delta = \frac{x_{max} - x_{min}}{D}, \tag{12}$$

with x_{min} and x_{max} representing the minimum and maximum values in the series, respectively, and D denoting the discretization level.

After symbolizing the first column of the embedding vectors $S_{t,1}$, the subsequent elements are symbolized relative to the first quantized element. For each embedding vector, the quantized symbols for subsequent elements are computed as follows:

$$S_{t,k}=S_{t,1}+\lfloor\frac{\vec{X}_{t,k}^{d_E,\tau}-\vec{X}_{t,1}^{d_E,\tau}}{\Delta}\rfloor, 1\le t\le N-\left(d_E-1\right)\tau, 2\le l\le d_E. \tag{13}$$

This procedure results in a symbolic pattern matrix S, where each row represents a quantized ordinal pattern π_i^U. The probability distribution $p\left(\pi_i^U\right)$ of these quantized patterns is calculated by counting occurrences and normalizing by the total number of patterns:

$$p\left(\pi_i^U\right)=\frac{\#\left\{S_t^{d_E,\tau}\vee S_t^{d_E,\tau}\ corresponds\ \text{to}\ pattern\ \pi_i^U\right\}}{N-\left(d_E-1\right)\tau}, i=1,\ldots,D^{d_E}. \tag{14}$$

The UPEn is then computed similarly to ShEn, with normalization to ensure values range between 0 and 1:

$$UPEn\left(X\right)^{d_E,\tau,D}=\frac{-1}{\ln D^{d_E}}\sum_{i=1}^{D^{d_E}}p\left(\pi_i^U\right)\ln p\left(\pi_i^U\right), \tag{15}$$

where the normalization factor $\ln D^{d_E}$ represents the theoretical maximum entropy achievable under a uniform pattern distribution.

Parameter selection is crucial in UPEn analysis. Typically, an embedding dimension $d_E=3$ is employed, balancing computational simplicity and capturing realistic dynamics of most real-world signals. Additionally, a delay parameter $\tau=1$ is chosen to preserve the structural integrity of sequential observations [32]. The discretization level D significantly influences the performance of UPEn. A higher retains more amplitude detail, enhancing sensitivity but also increasing susceptibility to noise and requiring larger sample sizes for stability. Conversely, lower values of D provide noise robustness at the expense of amplitude resolution. Chen et al. [31] recommend a discretization level of $D=4$ for practical applications such as financial crash detection, providing an optimal compromise between detail preservation and robustness.

3. Methods and Empirical Results

To comparatively evaluate classical PEn and its variants, as well as to identify potential early-warning indicators of cryptocurrency market crashes, we specifically focus on the significant Bitcoin market crash period spanning from August 21, 2017, to April 3, 2018. This period includes the well-documented speculative bubble burst at the end of 2017 and early 2018, which provides an exemplary scenario for studying complexity dynamics within cryptocurrency markets.

The analysis utilizes daily Bitcoin price data, transformed into standardized returns to ensure stationarity and comparability across entropy measures. The returns are computed as:

$$G\left(t\right)=\frac{x\left(t+\Delta t\right)-x\left(t\right)}{x\left(t\right)}, \tag{16}$$

and subsequently standardized as:

$$g\left(t\right)=\frac{G\left(t\right)-\langle G\rangle}{\sigma}, \tag{17}$$

where $\langle G\rangle$ denotes the mean and σ the standard deviation of returns G.

All computational analyses in this study were executed using the Python programming language within the Jupyter Notebook interactive environment. Implementation of the entropy calculation methods, including permutation entropy variations, leveraged the Entropy Hub software package [33], ensuring consistency and reproducibility of the results.

A sliding window technique was adopted for calculating entropy values, facilitating a dynamic and temporal assessment of complexity changes. Specifically, the chosen window length was $w=50$ days, determined through preliminary experimentation as optimal for capturing significant complexity fluctuations during the studied Bitcoin crash period. The window was incrementally shifted along the time series with a step of $\Delta t=1$, allowing a comprehensive temporal analysis.

Comparing the dynamics of the actual Bitcoin returns and corresponding entropy measures provides insights into complexity trends that precede and characterize market crashes. Consistent complexity behavior patterns, such as noticeable rises or drops during the pre-crash phase, could serve as reliable precursor indicators for impending market disruptions [34, 35, 36, 37, 38]. These findings contribute to the broader understanding of cryptocurrency market behavior, enhancing predictive capabilities and risk management strategies.

In Figure 1, we present the comparative dynamics of Bitcoin prices (BTC-USD) alongside the classical PEn metric during the critical period spanning from August 21, 2017, to April 3, 2018. The dashed green line marks December 6, 2017, indicating the onset of the major Bitcoin market crash.

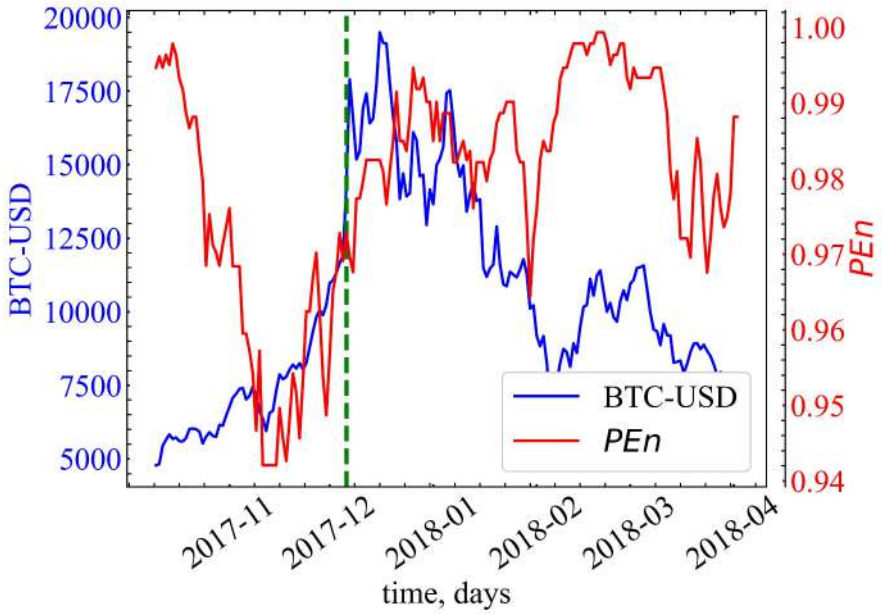

Figure 1: Comparative dynamics of the Bitcoin market crash (2017-2018) and the standard PEn

Initially, from late August to early December 2017, Bitcoin prices exhibit an exponential upward trend, reaching unprecedented highs and reflecting market optimism and speculative interest. During this pre- crash phase, the classical permutation entropy metric remains relatively high, indicative of significant market complexity and unpredictability, characteristic of dynamically healthy cryptocurrency markets. Approaching early December 2017, Bitcoin price growth accelerates sharply, reaching its historical peak. Correspondingly, the PEn measure begins a notable and rapid decrease from its previously elevated values, signaling a crucial shift from a highly complex state to increasingly predictable dynamics. This reduction in entropy clearly precedes the actual crash, highlighting the emergence of ordered patterns within price movements. Such a drop in complexity implies that market participants' behavior is becoming more synchronized and less diverse, reflecting reduced market efficiency and heightened systemic risk.

Following the green dashed line marking December 6, 2017, Bitcoin prices rapidly decline, marking the onset of the cryptocurrency market crash characterized by high volatility and investor uncertainty. During this crash period, permutation entropy continues to decline and reaches its lowest values, underscoring significantly increased predictability and reduced market complexity. This entropy minimum effectively coincides with the deepest market downturns, capturing the peak synchronization of trader behavior indicative of panic-driven selling and herd-like market dynamics.

After the steepest phase of the crash, beginning approximately mid-February 2018, Bitcoin prices start to stabilize and gradually recover, though remaining volatile due to ongoing uncertainty. In parallel, the PEn values gradually recover, reflecting the slow return of market complexity and efficiency. The increasing entropy during this recovery phase suggests that diverse market behaviors and a broader range of trading strategies are slowly being restored, signaling a cautious re-emergence of market resilience.

In summary, Figure 1 emphasizes the potential utility of classical permutation entropy as an early indicator for cryptocurrency market crashes. Its distinctive temporal pattern – high entropy during stable market growth, rapid entropy decrease preceding the crash, minimal entropy at the crash peak, and a gradual entropy recovery afterward – provides valuable insights for traders, investors, and policymakers concerned with predicting and managing risks associated with cryptocurrency market instability.

Figure 2 illustrates the comparative dynamics of Bitcoin prices (BTC-USD) and the WPEn metric during the Bitcoin market crash period from August 21, 2017, to April 3, 2018. The dashed green vertical line denotes December 6, 2017, the identified starting point of the significant crash in Bitcoin prices.

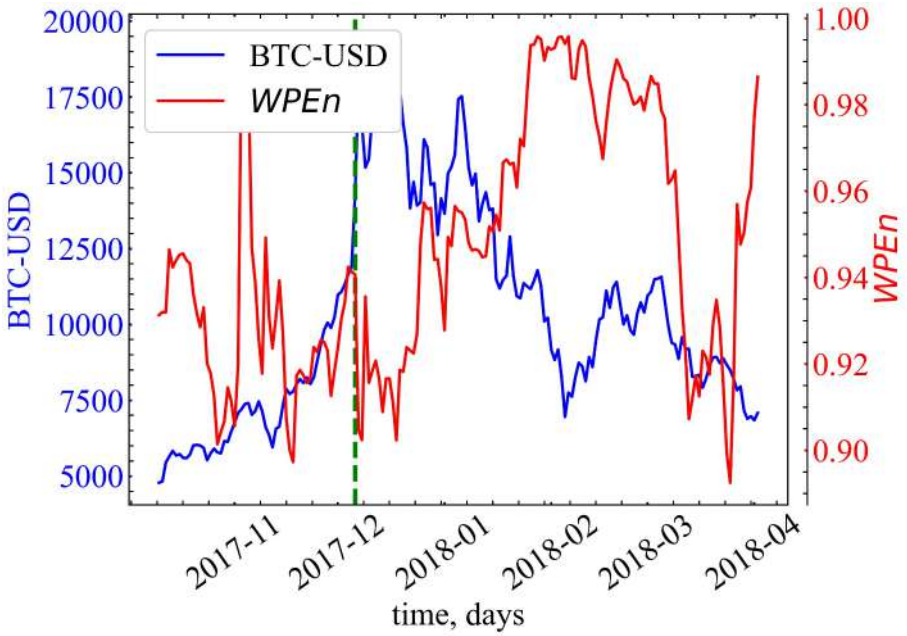

Figure 2: Comparative dynamics of the Bitcoin market crash (2017-2018) and the WPEn

In contrast to classical PEn, WPEn explicitly incorporates amplitude variations, assigning greater importance to patterns derived from subsequences with significant variance or energy. This property enables WPEn to detect and reflect subtle yet crucial fluctuations in market volatility and price amplitude, providing additional depth to complexity analysis in cryptocurrency markets.

During the pre-crash period from late August to early December 2017, Bitcoin prices rose substantially, reaching historical highs amid strong market enthusiasm and speculative activities. WPEn values remained relatively elevated throughout this phase, indicating a highly complex and diverse market environment characterized by dynamic interactions among market participants without dominant or overly coordinated patterns.

As the market approaches early December 2017, WPEn exhibits notable and sharp fluctuations, corresponding closely with significant price movements in Bitcoin. Unlike the gradual decline seen in classical PEn, WPEn demonstrates abrupt drops associated directly with intense volatility events and pronounced amplitude variations. These sudden entropy reductions reflect rapid transitions toward less complex and more predictable market dynamics, capturing critical moments of increased instability immediately preceding and during the early phases of the crash.

At the peak of the crisis (around late December 2017 to January 2018), WPEn values reach their lowest points, aligning precisely with the most severe declines in Bitcoin prices. This pronounced entropy drop illustrates the increased market synchronization and collective investor behavior, typical of panic-driven sell-offs, and highlights WPEn's sensitivity to substantial amplitude and volatility shifts. Following the main phase of the crash, Bitcoin prices enter a volatile recovery period,

accompanied by rapid increases and fluctuations in WPEn. The post-crisis recovery shows multiple sharp entropy variations, indicating persistent periods of instability and uncertainty in market dynamics. These fluctuations underscore the continued vulnerability and complexity of the cryptocurrency market as it attempts to regain equilibrium.

In summary, Figure 2 demonstrates WPEn's capability to detect immediate market instabilities and significant amplitude variations effectively. While WPEn does not provide as clear an anticipatory signal as classical PEn, its acute responsiveness to abrupt market fluctuations makes it a powerful analytical tool for identifying and characterizing critical moments of cryptocurrency market instability.

Figure 3 presents a comparative analysis of Bitcoin prices (BTC-USD) alongside the AAPEn metric for the period from August 21, 2017, to April 3, 2018. The green dashed line marks December 6, 2017, denoting the onset of the Bitcoin market crash.

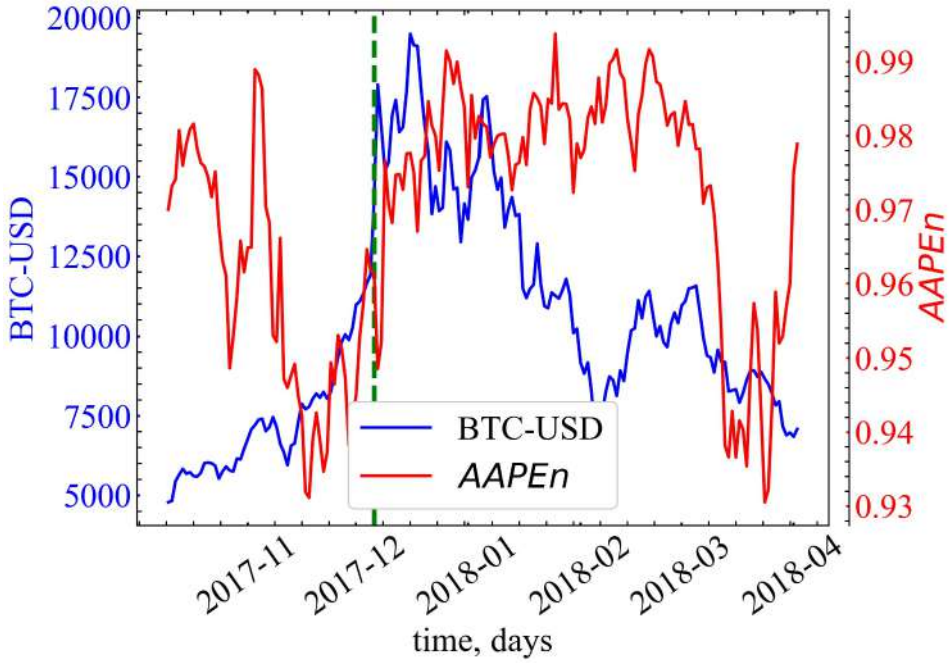

Figure 3: Comparative dynamics of the Bitcoin market crash (2017–2018) and the AAPEn

Unlike classical PEn and weighted permutation entropy (WPEn), the amplitude-aware permutation entropy explicitly considers amplitude differences between consecutive data points, enhancing its sensitivity to detect significant structural shifts and sudden anomalies in market behavior.

In the pre-crash period, spanning from late August to early December 2017, Bitcoin prices experience rapid growth and pronounced volatility. During this phase, AAPEn values remain elevated, indicative of a complex and diverse market state characterized by relatively unsynchronized market participant behavior. High AAPEn values here reflect a healthy market condition without clear early warnings of the impending crash.

As the market approaches early December 2017, AAPEn exhibits more pronounced fluctuations and begins a discernible downward trend. This early entropy decline, particularly noticeable before the actual onset of the crash (marked by the green dashed line), underscores AAPEn's sensitivity and effectiveness in capturing subtle, amplitude-driven market disturbances. Thus, AAPEn provides valuable precursor signals of rising market instability earlier than traditional entropy metrics.

At the crash peak between December 2017 and January 2018, Bitcoin prices sharply decline, and concurrently, AAPEn significantly decreases, reaching its minimum values. This drop clearly illustrates the transition toward more predictable, amplitude-coordinated patterns arising from synchronized panic-driven selling behaviors, characteristic of severe market crises.

In the subsequent recovery phase, from late January to April 2018, AAPEn demonstrates partial recovery toward higher complexity levels, albeit with substantial fluctuations reflecting continued market uncertainty and episodes of heightened volatility. These entropy fluctuations during the recovery phase underscore the lingering instability within the cryptocurrency market as it attempts to regain equilibrium.

Overall, Figure 3 highlights the superior capability of amplitude-aware permutation entropy in detecting and interpreting nuanced market dynamics. Its sensitivity to subtle amplitude fluctuations allows it to serve effectively as both an early-warning indicator and a detailed analytical tool, offering deeper insights into the structural and behavioral complexities of cryptocurrency markets during periods of significant turbulence.

Figure 4 presents the comparative dynamics of Bitcoin prices (BTC-USD) and the UPEn metric from August 21, 2017, to April 3, 2018. The green dashed line indicates December 6, 2017, marking the onset of the significant Bitcoin market crash.

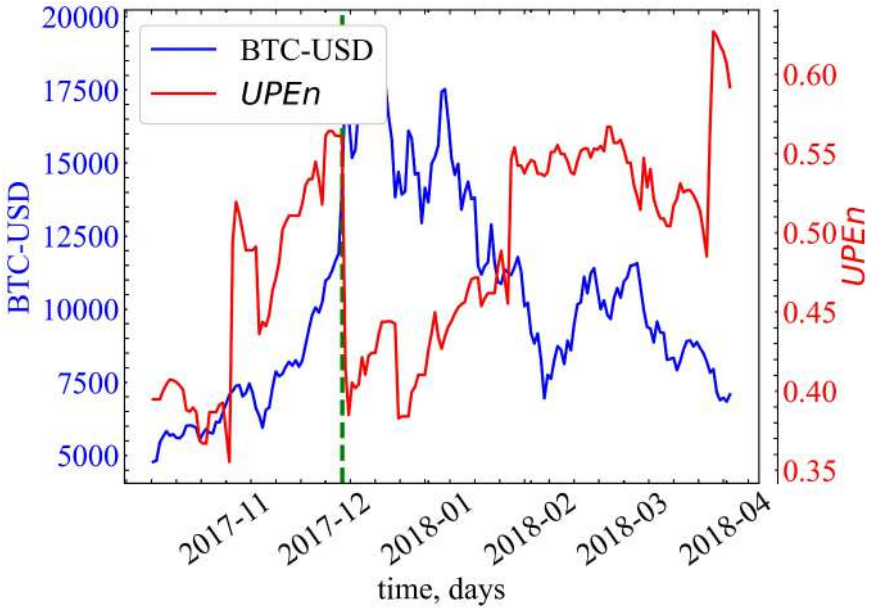

Figure 4: Comparative dynamics of the Bitcoin market crash (2017–2018) and the UPEn

Unlike traditional permutation entropy approaches, UPEn utilizes uniform quantization to explicitly incorporate amplitude information and address the issue of equal-value observations. This allows UPEn to provide a more robust and stable complexity representation by effectively capturing longer-term structural changes in market dynamics while minimizing sensitivity to minor fluctuations.

In the initial period from late August to early December 2017, Bitcoin prices steadily rise amid market optimism and speculative activities, accompanied by moderate volatility. UPEn values during this phase gradually increase, reflecting growing market complexity and active dynamics, though remaining relatively stable and moderate overall. This stability indicates balanced complexity conditions without immediate signs of market distress.

As the Bitcoin market approaches early December 2017, the UPEn metric begins to exhibit a discernible decline, signaling the early emergence of structural instability preceding the crash. Unlike the more volatile behavior seen in classical or amplitude-aware permutation entropy metrics, UPEn's decline is smoother and more gradual, effectively filtering short-term volatility while emphasizing longer-term market changes.

During the peak crash period between December 2017 and January 2018, Bitcoin prices experience rapid declines. Correspondingly, UPEn reaches its lowest point, clearly reflecting diminished market complexity and increased predictability resulting from coordinated, panic-driven selling behavior. This minimum entropy period effectively captures the structural transition from a complex, healthy market to a more ordered but fragile state characteristic of crisis conditions.

In the post-crash recovery phase, beginning around February 2018, UPEn gradually increases, indicating a slow yet consistent restoration of market complexity and stability. Compared to other permutation entropy methods, UPEn shows fewer abrupt fluctuations during this recovery phase, suggesting it effectively emphasizes sustained structural recovery rather than short-term volatility. This characteristic makes UPEn particularly valuable for detecting and interpreting the longer-term complexity evolution in cryptocurrency markets during periods of recovery and restabilization.

Overall, Figure 4 underscores the effectiveness of UPEn as a reliable, robust indicator for capturing structural complexity changes associated with cryptocurrency market crashes. Its capability to

highlight gradual complexity shifts and filter short-term noise makes UPEn highly suitable for policymakers, investors, and analysts aiming for stable and long-term market stability indicators.

4. Conclusion

In this paper, we performed a comprehensive comparative analysis of classical permutation entropy (PEn) and its enhanced variants – weighted permutation entropy (WPEn), amplitude-aware permutation entropy (AAPEn), and uniform quantization-based permutation entropy (UPEn) – specifically applied to the Bitcoin market crash from August 21, 2017, to April 3, 2018. Our primary goal was to evaluate the effectiveness of these entropy measures as early-warning indicators of cryptocurrency market instability, overcoming traditional PEn's limitation of disregarding amplitude information.

Our empirical findings underscore the unique strengths of each entropy method in capturing distinct aspects of cryptocurrency market dynamics. The classical PEn measure proved notably effective in detecting a gradual complexity decline prior to the crash, accurately reflecting the transition from a complex and efficient market to a predictable and vulnerable state. Its ability to identify reduced entropy preceding the actual market downturn highlights its robustness as a reliable precursor metric for cryptocurrency market crashes.

The WPEn metric, through its variance-based weighting of ordinal patterns, demonstrated significant sensitivity to abrupt market fluctuations, capturing immediate instability events with notable precision. Although WPEn was less effective in identifying gradual complexity reductions compared to classical PEn, its rapid responsiveness makes it particularly valuable for real-time detection of severe volatility episodes typical in cryptocurrency markets.

AAPEn emerged as exceptionally effective due to its refined incorporation of amplitude differences among consecutive data points. It captured subtle but meaningful market shifts with greater sensitivity and offered more transparant early-warning signals compared to both classical PEn and WPEn. The flexibility in tuning its parameters also enhances its adaptability to diverse cryptocurrency market conditions, improving predictive accuracy and interpretability regarding structural shifts and emerging instabilities. UPEn, leveraging uniform quantization to incorporate amplitude data, provided stable and robust indicators by emphasizing sustained structural changes while effectively filtering out short-term volatility. Although less sensitive to immediate fluctuations compared to WPEn or AAPEn, UPEn was particularly effective in revealing longer-term complexity trends, making it highly suitable for strategic monitoring of cryptocurrency markets over extended periods.

Overall, our analysis confirms the utility of permutation entropy methods, especially amplitude-enhanced variants, as powerful tools for predicting and analyzing cryptocurrency market crashes. While classical PEn continues to serve as a straightforward and reliable early indicator, advanced entropy measures such as WPEn, AAPEn, and UPEn significantly enrich the analytical toolkit by capturing deeper market complexities and subtle signals of impending instability.

Future research directions include applying these entropy methodologies to analyze other cryptocurrency crashes and market anomalies, exploring their applicability across diverse digital assets and market conditions. Integrating these entropy metrics with advanced machine learning algorithms, including deep learning techniques, could further improve forecasting precision and enable the development of sophisticated real-time alert systems for cryptocurrency market monitoring. Additionally, exploring multivariate extensions of these entropy measures may provide deeper insights into interdependencies and collective dynamics among different cryptocurrencies, further enhancing their value as decision-support tools for investors, market analysts, and regulatory authorities. Furthermore, combining entropy-based complexity analysis with clustering techniques may provide novel insights into market regime identification and trading strategy optimization, ultimately leading to better-informed trading decisions and improved risk management practices in cryptocurrency markets [39].

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Comparative Evaluation of StyleGAN3-Based Augmentation Strategies for Enhanced Medical Image Classification

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Abstract

Deep learning models for medical image classification face significant challenges due to class imbalance and the limited availability of annotated datasets, particularly for rare diseases. Traditional data augmentation techniques, such as rotation, translation, etc., often fail to provide sufficient diversity to perform a good classification for minor classes. To address this issue, various strategies have been explored, including oversampling, undersampling, cost-sensitive learning, and synthetic data generation using generative adversarial networks (GANs). In this study, we evaluate the impact of using a generative AI based approaches and demonstrate that the most effective strategy is to combine synthetic augmentation with traditional methods. Specifically, we employ StyleGAN3 to generate high-fidelity synthetic images that, when integrated with traditional data-augmentation techniques, may improve the performance of deep learning models on medical image classification. We validate our method on datasets, including COVID-19 chest X-rays and HAM10000. Experimental results show that this hybrid approach leads to an improvement in classification accuracy, particularly for minority classes, surpassing standalone augmentation strategies. Our findings highlight the potential of AI-driven synthetic data generation as a complementary solution to traditional augmentation, offering a more balanced and diverse dataset for medical image analysis.

Keywords

Medical imaging, Data augmentation, Generative Adversarial Networks, StyleGAN, Class imbalance

1. Introduction

In the field of deep learning for medical imaging, one of the significant challenges is class imbalance coupled with small annotated data. It is especially challenging when working with rare diseases, where the low occurrence and brief duration of the appearance of symptoms can make the collect of data difficult, which may affect the quality of the model training.

As a result, such a deficiency affects classification model performance, particularly in classifying complicated pathologies that are important even their rarity in the datasets. This asymmetry degrades the performance of the model in favor of the majority classes, thus decreasing the precision and reliability of the predictions compared to the minority classes.

The imbalance datasets, coupled with the limited availability of annotated datasets, presents obstacles to the development of efficient and high-quality models in the field of medical imaging. Traditional classification models become overfitted to the dominant classes, leading to a significant loss of accuracy for the minority classes. While traditional data augmentation techniques such as rotation, resizing, and cropping—are often applied to alleviate this issue, they often fail to generate the necessary diversity and do not notably enhance the generalization capacity of the models.

Classical data augmentation techniques [1], such as rotation, flipping, scaling, and cropping, are widely used to artificially increase the size of training datasets and improve model generalization. These methods help in introducing minor variations to the images, making the model more robust to small transformations. However, they have significant limitations, especially in the medical imaging domain. Since medical images often contain complex and subtle patterns that are crucial for diagnosis, simple transformations may not sufficiently capture the variability needed to enhance model performance. Furthermore, these techniques do not create new pathological patterns but merely

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modify existing ones, limiting their effectiveness in addressing class imbalance. As a result, they may not significantly improve the classification of rare diseases, which require more sophisticated augmentation strategies capable of generating realistic and diverse samples.

To address class imbalance in deep learning, various strategies can be employed (see [2] for an exhaustive review).

1. Oversampling Methods: Oversampling techniques aim to increase the representation of minority- class samples to balance the dataset. Synthetic Minority Over-sampling Technique (SMOTE) and its variants generate synthetic data points to improve class distribution [3, 4]. Additionally, data augmentation techniques introduce transformed versions of existing images to improve model generalization. While oversampling has been shown to be one of the most effective techniques for CNN-based classification [5], its effectiveness can be limited on images in general and for medical imaging.
2. Undersampling Methods: In contrast, undersampling reduces the number of majority-class samples to achieve a more balanced dataset, thereby improving class proportions and reducing computational cost. Random undersampling removes a subset of majority samples, while more advanced techniques, such as cluster-based undersampling, aim to retain the most informative samples. Although undersampling is effective in extreme imbalance scenarios, it may lead to information loss, particularly in complex medical datasets [5].
3. Other Learning Approaches: Beyond sampling strategies, cost-sensitive learning modifies the loss function to assign higher penalties for misclassifications in the minority class, with focal loss being a notable example that prioritizes hard-to-classify instances [6, 7]. Ensemble learning improves prediction accuracy by combining multiple classifiers, but its high computational cost can be prohibitive [8]. Hybrid approaches integrate data-level and algorithm-level solutions, such as clustering with sampling techniques or cost-sensitive learning with neural networks. Semi-supervised and self-supervised learning leverage unlabeled data to enhance feature representation and generalization, while deep metric learning and contrastive learning focus on learning more discriminative representations without altering class distribution. Each of these methods has trade-offs in efficiency, robustness, and complexity, so a choice can be made based on the nature of the dataset and the nature of application demands.

To overcome the limitations of traditional imbalance-handling techniques, AI-based image-generation methods [9, 10, 11, 12, 13], and particularly StyleGAN [14, 15, 16], have emerged as a groundbreaking solution for generating realistic synthetic medical images. StyleGAN's ability to produce high-fidelity images enables dataset augmentation without compromising the valuable pathological characteristics essential for medical imaging. By generating samples for underrepresented classes, StyleGAN helps mitigate class imbalances and improves the stability of classification models.

In this work, we introduce a StyleGAN3-based data augmentation approach that combines state-of-the- art generative modeling with classical balancing techniques to enhance the diversity and representation of minority-class samples. StyleGAN3, with its improved spatial coherence, is particularly well-suited for medical image synthesis, preserving intricate morphological features of pathological conditions. Unlike conventional oversampling methods that risk overfitting, our approach generates diverse and realistic synthetic samples, enriching the dataset and improving the generalization of classification models. By training StyleGAN3 on the minority class, we aim to restore class balance, enhance dataset variability, and ultimately improve the robustness of medical image classification systems.

This paper is structured as follows: Section 2 is a literature review of data augmentation and GANs in medical imaging. Section 3 is a description of the methodology of our work, including data preprocessing, model architecture, and performance metrics. Section 4 is the experimental results and their discussion. Section 5 concludes the paper and gives future directions of research

2. Related Works

2.1. Based on the Covid_19 Radiography Dataset

Abdul Waheed et al. [17] introduced CovidGAN, an ACGAN-based model generating synthetic chest X-ray (CXR) images to address data scarcity in medical imaging. Trained on three datasets (IEEE

Covid Chest X-ray, COVID-19 Radiography Database, COVID-19 Chest X-ray Dataset), CovidGAN improved CNN classification accuracy from 85% to 95% with augmented data.

Sharmila V J et al. [18] proposed a DCGAN-CNN hybrid for classifying CXR images (normal, pneumonia, COVID-19). The DCGAN generates 64×64 synthetic images, later resized for classification. The CNN, comprising eight convolutional layers, achieved accuracy between 94.8% and 98.6%, surpassing AlexNet and GoogLeNet.

2.2. Based on the HAM10000 Dataset

Bilal Ahmad et al. [19] developed TED-GAN, a hybrid VAE-GAN approach for skin lesion image generation. Using a dual-GAN framework, their model significantly improved melanoma classification, increasing sensitivity from 53% to 82% and specificity from 75% to 94%.

Qinchen Su et al. [20] introduced STGAN, a GAN-based augmentation method for multi-class imbalanced skin lesion classification. Trained on the HAM10000 dataset, it improved FID, Inception Score, Precision, and Recall over StyleGAN2 and achieved an accuracy of 98.23% with a ResNet50 classifier.

2.3. Based on Other Datasets

Bilal Ahmad et al. [21] proposed VAE-GAN, leveraging informative noise instead of Gaussian noise for brain tumor image generation. Applied to 3,064 CE-MR images, their approach boosted classification accuracy from 72.63% to 96.25%.

Guilherme C et al. [22] implemented StyleGAN2-ADA, enhancing image quality for fundus imaging via adaptive discriminator augmentation to mitigate data scarcity and imbalance.

Table 1
Summary of Related Works

Study	Methodology	Dataset	Accuracy	Year
Waheed et al. [17]	CovidGAN (ACGAN)	COVID-19 Radiography	95%	2020
Sharmila et al. [18]	DCGAN-CNN	COVID-19 Radiography	94.8%-98.6%	2021
Ahmad et al. [19]	TED-GAN (VAE-GAN)	HAM10000	Sensitivity: 82%	2022
Su et al. [20]	STGAN	HAM10000	98.23%	2021
Ahmad et al. [21]	VAE-GAN (Brain Tumors)	CE-MR Brain Tumor	96.25%	2023
Guilherme et al. [22]	StyleGAN2-ADA	Fundus Imaging	85%	2021

3. Proposed Approach

Our approach stands out by leveraging GANs not only for data augmentation but also for dataset balancing. To ensure fair evaluation and prevent data leakage, our dataset was initially divided into 80% for training and 20% for testing. This split remains consistent across all experiments, and transformations are applied only to the test set. We conducted our study on two medical imaging datasets: HAM10000 [23] and COVID-19 Radiography [24]. We propose four augmentation strategies:

1. Approach 1 - Traditional Data Augmentation Classical transformations (rotation, flipping, resizing) are applied to enhance training data diversity.
2. Approach 2 - Targeted Augmentation for Balancing Augmentation is applied specifically to minority classes to balance the dataset.
3. Approach 3 - StyleGAN3-Based Augmentation with Batch Injection Synthetic images generated by StyleGAN3 are injected into training batches to improve diversity.
4. Approach 4 - Hybrid StyleGAN3 Augmentation and Traditional Balancing A percentage of StyleGAN3-generated images is added, followed by traditional balancing techniques.

3.1. Approach 1: Traditional Data Augmentation

We apply standard transformations such as rotation, horizontal/vertical flipping, and color jittering before feeding images into ResNet50 and InceptionV3. Table 2 summarizes the transformations.

Table 2
Transformations applied for traditional augmentation

Transformation	Value
RandomHorizontalFlip	0.5
RandomVerticalFlip	0.5
RandomRotation	30°
ColorJitter	brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1 RandomAffine
RandomHorizontalFlip	0.5
RandomAffine	translate=(0.1, 0.1)

3.2. Approach 2: Targeted Augmentation for Balancing

This approach is inspired by Random Over-Sampling (ROS), a common technique for handling imbalanced datasets by duplicating samples from minority classes to match the distribution of majority classes. However, instead of simply duplicating existing images, we apply targeted data augmentation techniques (e.g., rotation, scaling, contrast adjustments) to generate new synthetic samples. The gener- ated images are saved and used to balance the dataset, ensuring that minority classes have the same number of images as the majority classes.

3.3. Approach 3: StyleGAN3-Based Augmentation with Batch Injection

StyleGAN3 is used to generate high-quality synthetic medical images that are directly injected into training batches during model training. Unlike traditional augmentation, which applies transformations to existing images, StyleGAN3 synthesizes new samples that mimic the distribution of real medical images.

In this approach, synthetic images are generated before training and dynamically included in mini-batches alongside real images. This ensures that the model learns robust representations by exposing it to a more diverse dataset. The dataset split remains unchanged, with synthetic images used only during training, preventing bias in the test evaluation.

3.4. Approach 4: Hybrid StyleGAN3 Augmentation and Traditional Balancing

This approach combines StyleGAN3-generated images with traditional dataset balancing techniques to optimize model performance. The augmentation process consists of two steps:

1. Generation of Synthetic Images: StyleGAN3 is used to generate additional images. We test four strategies by adding synthetic samples to the original training dataset, increasing the minority classes by 10%, 20%, 30%, and 40%, respectively.
2. Traditional Balancing Techniques: Once the synthetic images are added, classical balancing methods are applied. This includes oversampling the minority class and targeted augmentations (rotation, flipping, and intensity scaling) to equalize class representation.

This hybrid strategy ensures that the dataset remains well-balanced while introducing new variations through GAN-generated samples. The classifier is trained on the augmented dataset using ResNet50 and InceptionV3, and performance is evaluated based on classification metrics.

4. Results of data-augmentation

4.1. Results of StyleGAN3

The generated images show appreciable diversity in the characteristics of each class. This diversity is crucial to avoid overfitting and to improve the generalization of classification models by including realistic variations in the data.

Below, you will find samples of the images generated by StyleGAN3 for each minority class.

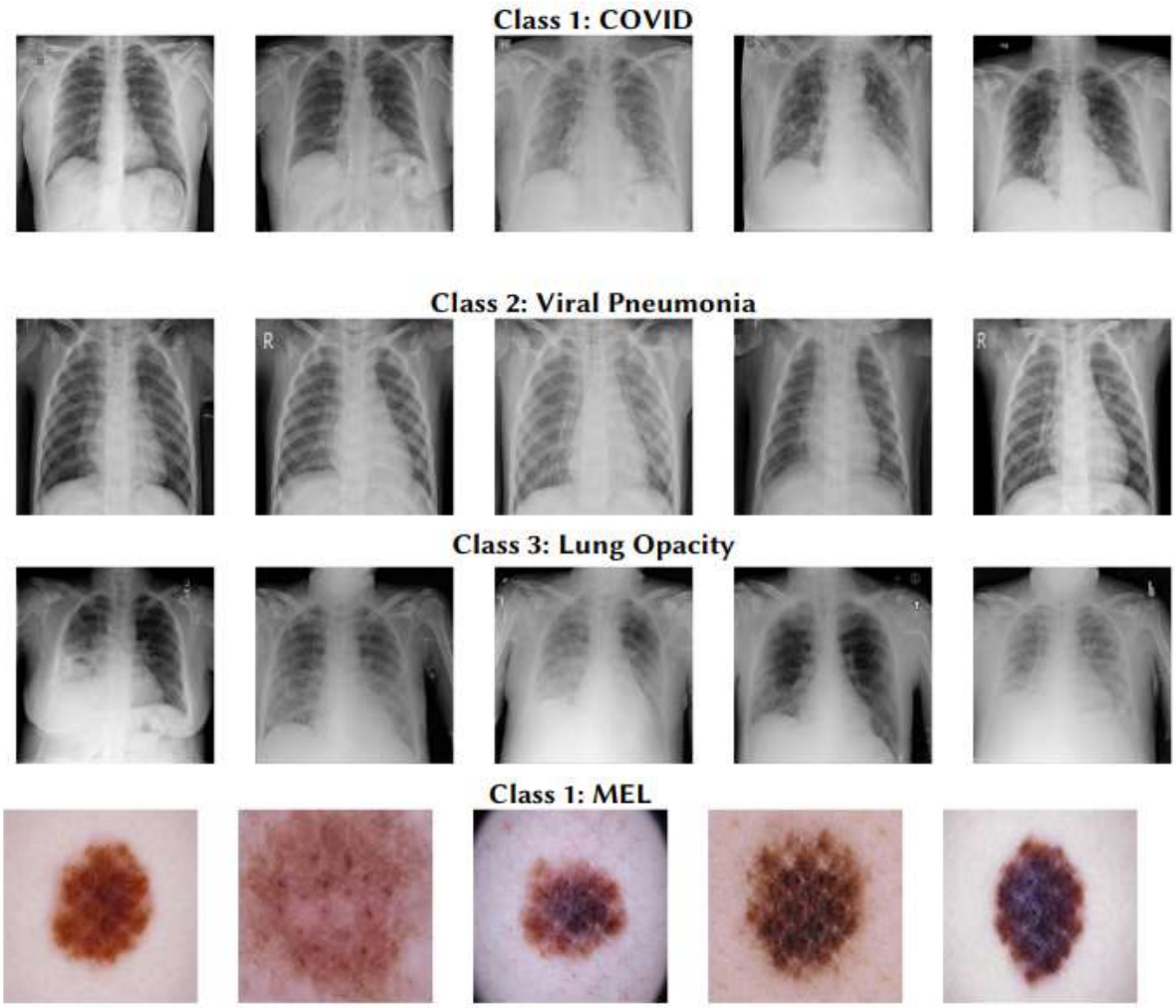


Figure 1: Images generated by StyleGAN3 for the COVID-19 related classes of the Covid-19 dataset and for HAM10000 MEL class.

4.2. Results of Augmentation

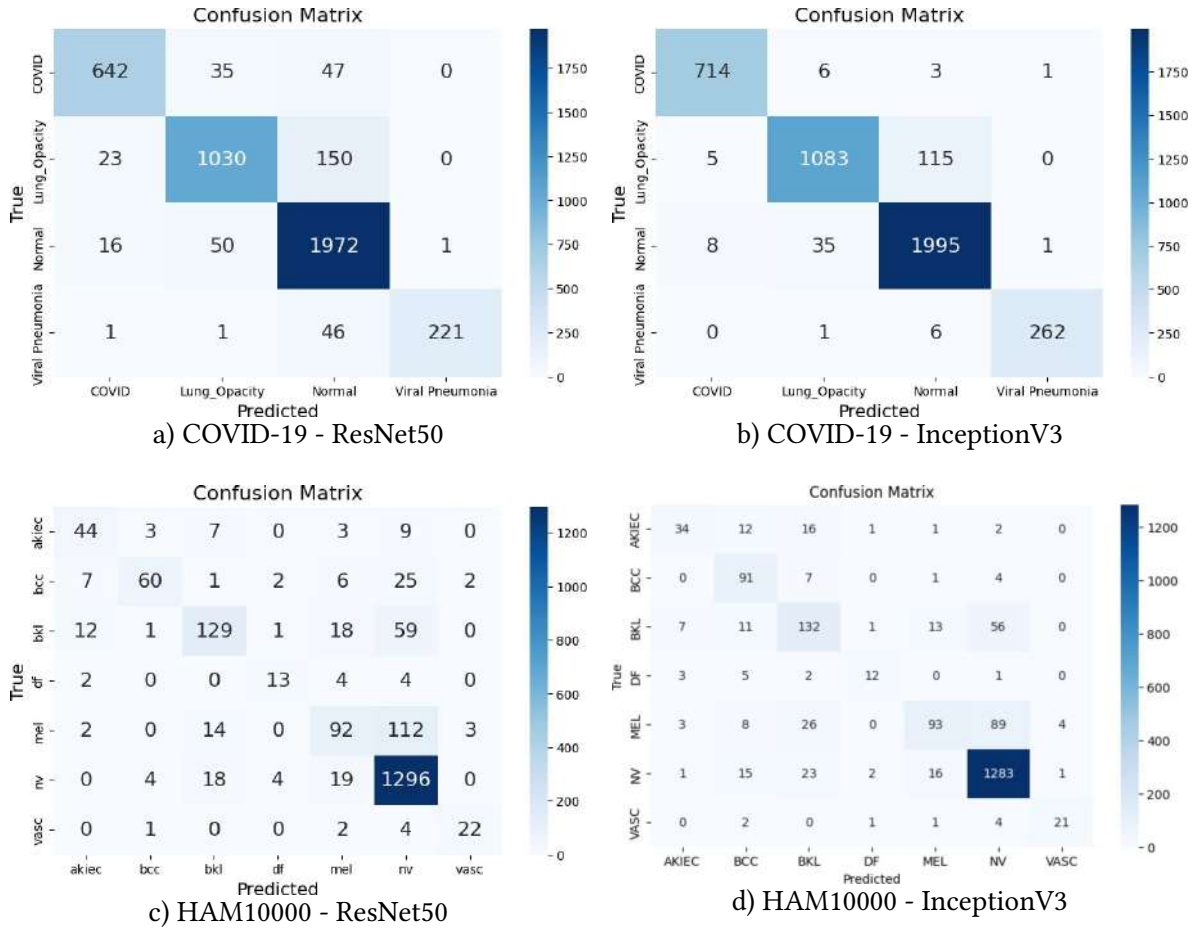
4.2.1. Approach 1: Traditional Augmentation

Table 3 presents the performance of the ResNet50 and InceptionV3 models on the COVID-19 Radiography and HAM10000 datasets using Approach 1, evaluated in terms of accuracy, recall, precision, and F1-score.

It is observed that the InceptionV3 model slightly outperforms the ResNet50 model in terms of accuracy and F1-score, achieving an accuracy of 94.82% compared to 91.26% for ResNet50 on the COVID-19 dataset and 82.49% compared to 81.48% on the HAM10000 dataset

Table 3
Performance results of the models with Approach 1: Traditional augmentation

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	91.26%	91.20%	91.26%	91.50%	82.59%	81.27%	82.59%	81.48%
InceptionV3	94.82%	94.84%	94.83%	94.88%	83.09%	82.02%	83.09%	82.49%



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 2: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets with Approach 1.

The confusion matrices in (see Figure 2) visualize the performance of the ResNet50 and InceptionV3 models on the COVID-19 Radiography and HAM10000 datasets using the traditional augmentation approach. They allow for evaluating the quality of each model's predictions on these two datasets in terms of correct and incorrect classifications.

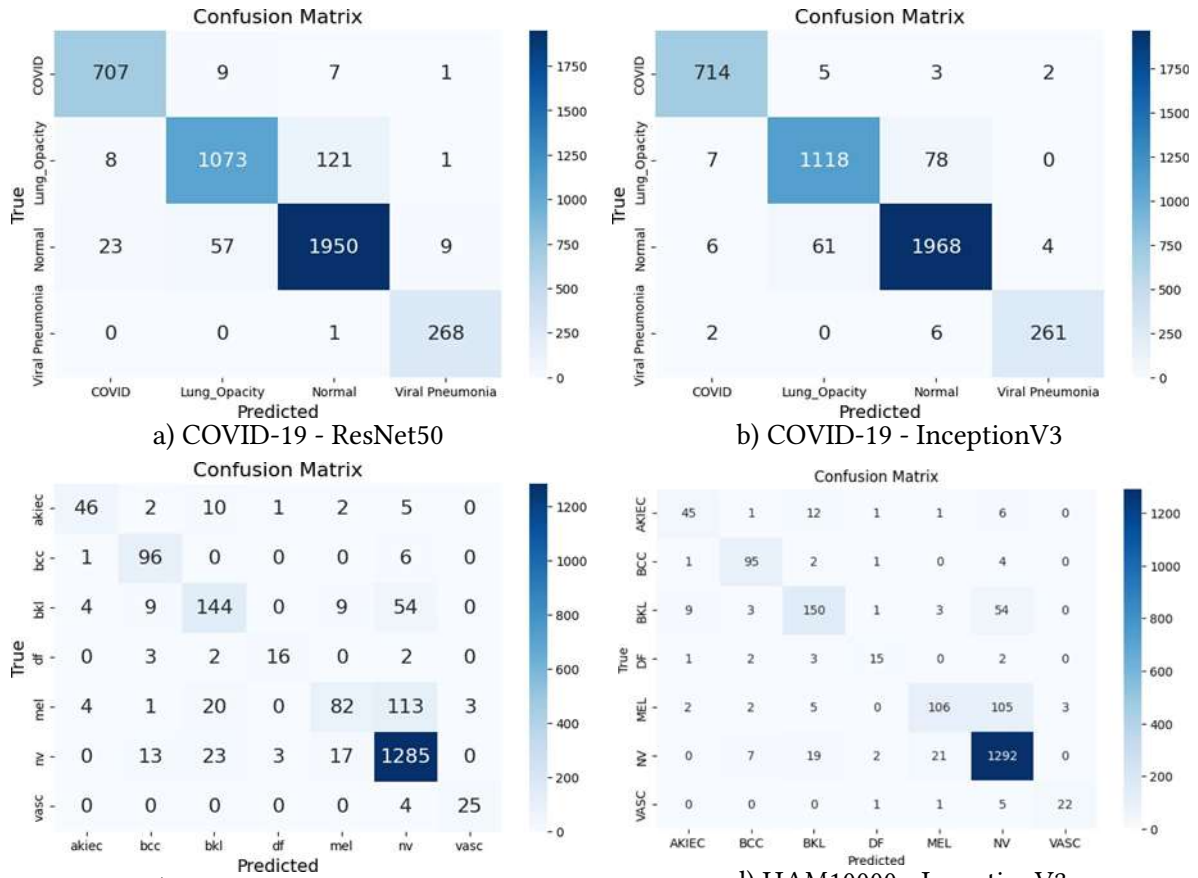
4.2.2. Approach 2: Traditional Data Augmentation with Balancing

Table 4 presents the performance of the ResNet50 and InceptionV3 models on the COVID-19 Radiography and HAM10000 datasets using Approach 2, evaluated in terms of accuracy, recall, precision, and F1-score.

It is noteworthy that the InceptionV3 model slightly surpasses the ResNet50 model in terms of accuracy and F1-score on the COVID-19 Radiography dataset, achieving an accuracy of 95.46% compared to 94.33% for ResNet50. Conversely, for the HAM10000 dataset, it is the ResNet50 model that displays better performance, achieving an accuracy of 83.19% compared to 71.77% for InceptionV3

Table 4
Performance results of the models with Approach 2: Traditional data augmentation with balancing

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	94.40%	94.37%	94.40%	94.40%	84.49%	84.49%	83.68%	83.16%
InceptionV3	95.89%	95.88%	95.89%	95.89%	86.03%	86.03%	85.11%	82.02%



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 3: Confusion matrices for ResNet50 and InceptionV3 on the COVID.

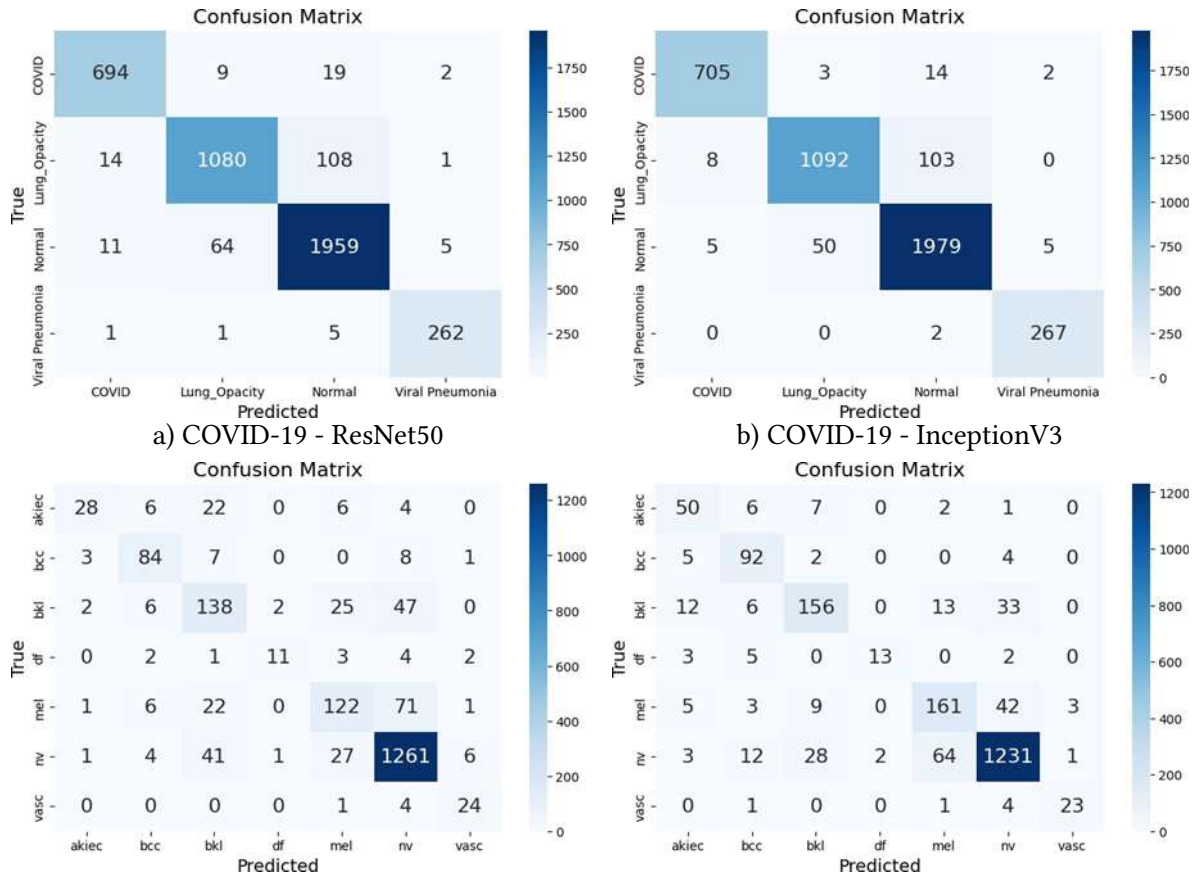
4.2.3. Approach 3: Augmentation using StyleGAN3 with Batch Injection

Table 5 presents the performance of the ResNet50 and InceptionV3 models on the COVID-19 Radiography and HAM10000 datasets using Approach 3, evaluated in terms of accuracy, recall, precision, and F1-score.

Table 5
Performance results of the models with Approach 2: Traditional data augmentation with balancing

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	94.33%	94.31%	94.33%	94.33%	83.19%	82.64%	83.19%	82.77%
InceptionV3	95.46%	95.45%	95.47%	95.48%	86.08%	86.19%	86.08%	86.54%

We observe that the InceptionV3 model slightly outperforms the ResNet50 model in terms of accuracy and F1-score on the COVID-19 Radiography dataset, achieving an accuracy of 95.46% compared to 94.33% for ResNet50. However, on the HAM10000 dataset, the InceptionV3 model also achieves better results with an accuracy of 86.08% compared to 83.19% for ResNet50 (see Figure 4 for the confusion matrices).



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 4: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets using Approach 3.

4.2.4. Approach 4: Augmentation using StyleGAN3 and Balancing with Traditional Methods

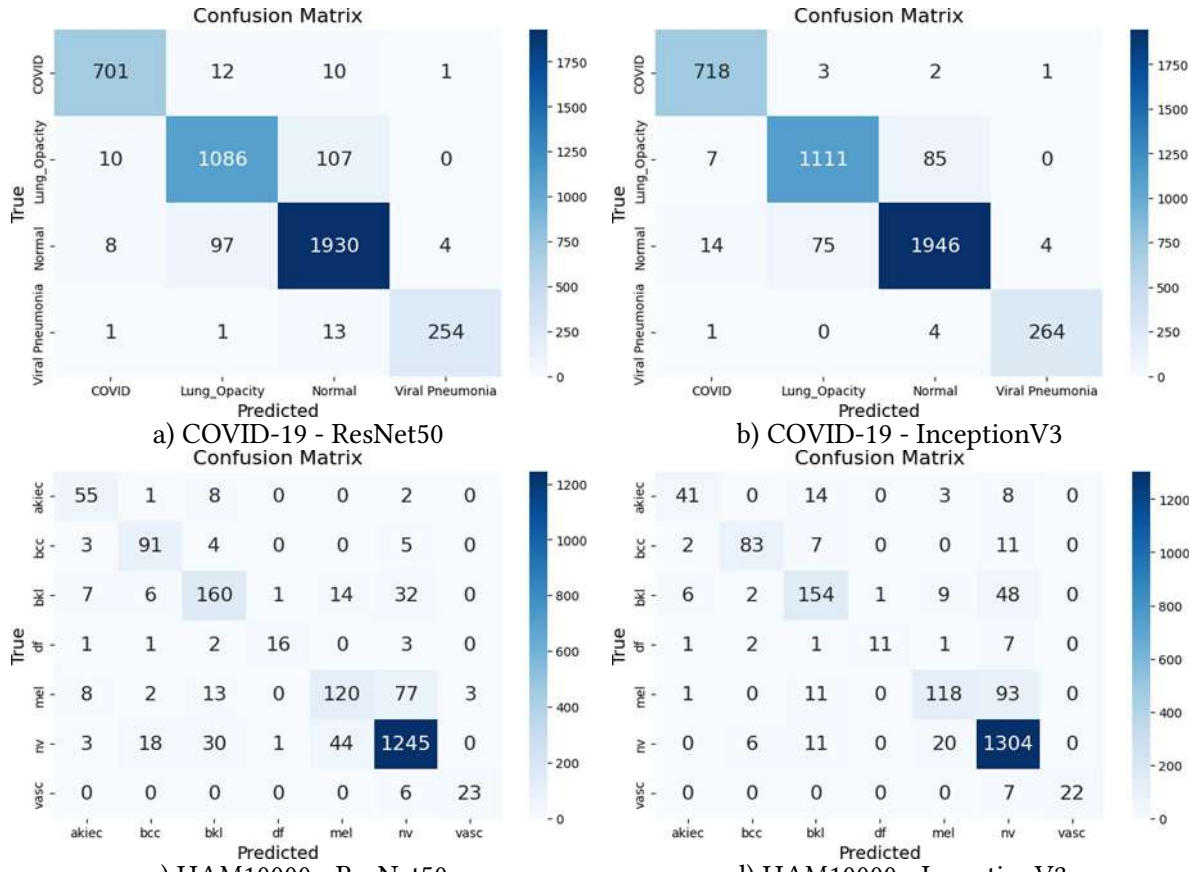
In this approach, we tested different levels of data augmentation, namely 10%, 20%, 30%, and 40%.

4.2.5. With 10% Augmentation

Table 6 presents the performance of the ResNet50 and InceptionV3 models on the COVID-19 Radiography and HAM10000 datasets with 10% data augmentation using Approach 4, evaluated in terms of accuracy, recall, precision, and F1-score.

Table 6
Performance results of the models with Approach 1: Traditional augmentation

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	93.76%	93.77%	93.77%	93.78%	85.28%	84.97%	85.29%	84.95%
InceptionV3	95.37%	95.36%	95.37%	95.36%	86.43%	85.61%	86.43%	85.96%



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 5: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets using Approach 4 with 10% augmentation.

Table 7

Model performance results with approach 4: augmentation by StyleGAN3 and balancing with traditional methods

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	94.49%	94.48%	94.50%	94.49%	83.99%	82.51%	83.99%	83.26%
InceptionV3	95.96%	95.96%	95.96%	95.96%	86.43%	86.20%	86.43%	86.14%

It is observed that the InceptionV3 model continues to outperform the ResNet50 model in terms of accuracy and F1-score with this approach on the COVID-19 Radiography dataset, achieving an accuracy of 95.84% compared to 94.49% for ResNet50. Furthermore, on the HAM10000 dataset, InceptionV3 also demonstrates better performance with an accuracy of 86.43% versus 83.99% for ResNet50.

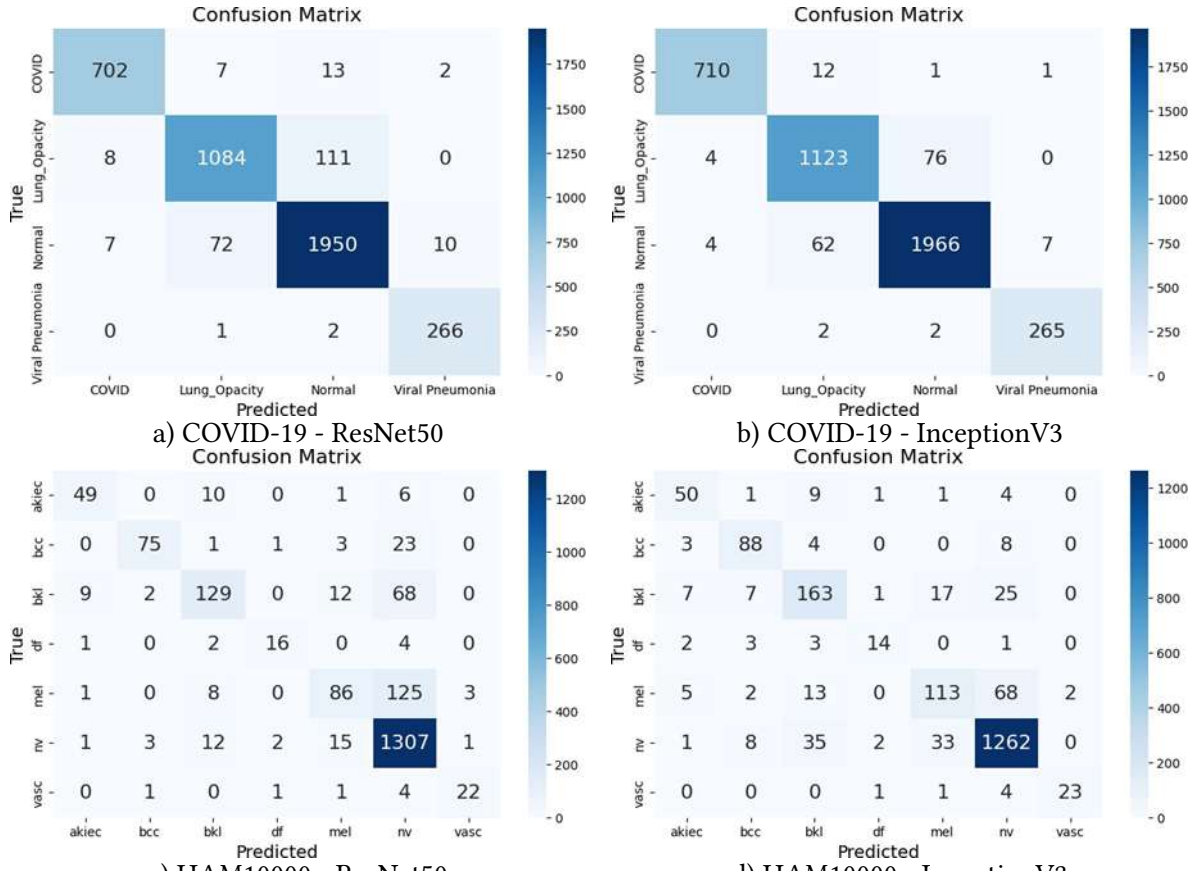
4.2.6. With 20% Augmentation

Table 8 presents the performance of the InceptionV3 and ResNet50 models on the COVID-19 Radiography and HAM10000 datasets with a 20% data augmentation using approach 4.

Table 8

Performance results of the models with approach 4: augmentation using StyleGAN3 and balancing with traditional methods

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	93.76%	93.75%	93.77%	93.75%	84.88%	84.31%	84.89%	84.22%
InceptionV3	95.58%	95.60%	95.58%	95.62%	85.73%	85.33%	85.74%	85.65%



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 6: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets with approach 4 at 30%.

It can be observed that in the COVID-19 Radiography dataset, InceptionV3 outperforms ResNet50 with an accuracy of 95.58% compared to 93.76%. The F1 scores, recall, and precision further confirm this trend, indicating better overall performance for InceptionV3.

Regarding the HAM10000 dataset, although the gap is smaller, InceptionV3 maintains an advantage with an accuracy of 85.73% compared to 84.88% for ResNet50. This difference demonstrates better handling of complex classes by InceptionV3.

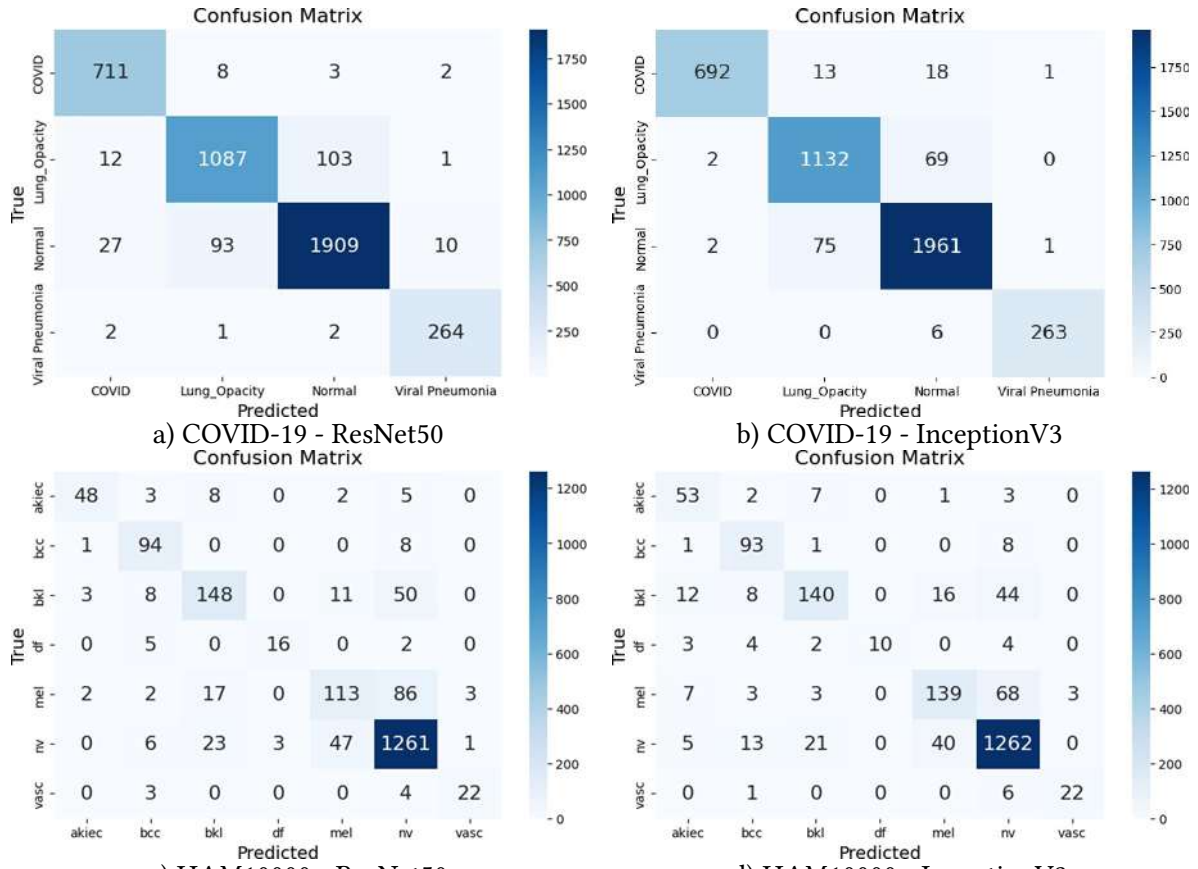
4.2.7. With 30% Augmentation

Table 9 presents the performance of the ResNet50 and InceptionV3 models on the COVID-19 Radiography and HAM10000 datasets with approach 4, evaluated in terms of accuracy, recall, precision, and F1-score.

Table 9
Performance results of the models with approach 4: augmentation using StyleGAN3 and balancing with traditional methods

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	94.49%	94.48%	94.50%	94.49%	83.99%	82.51%	83.99%	83.26%
InceptionV3	95.96%	95.96%	95.96%	95.96%	86.43%	86.20%	86.43%	86.14%

It can be noted that the InceptionV3 model continues to surpass the ResNet50 model in terms of accuracy and F1-score with this approach on the COVID-19 Radiography dataset, achieving an accuracy of 95.84% compared to 94.49% for ResNet50. Furthermore, on the HAM10000 dataset, InceptionV3 also demonstrates better performance with an accuracy of 86.43% compared to 83.99% for ResNet50.



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 7: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets with approach 4 at 20%.

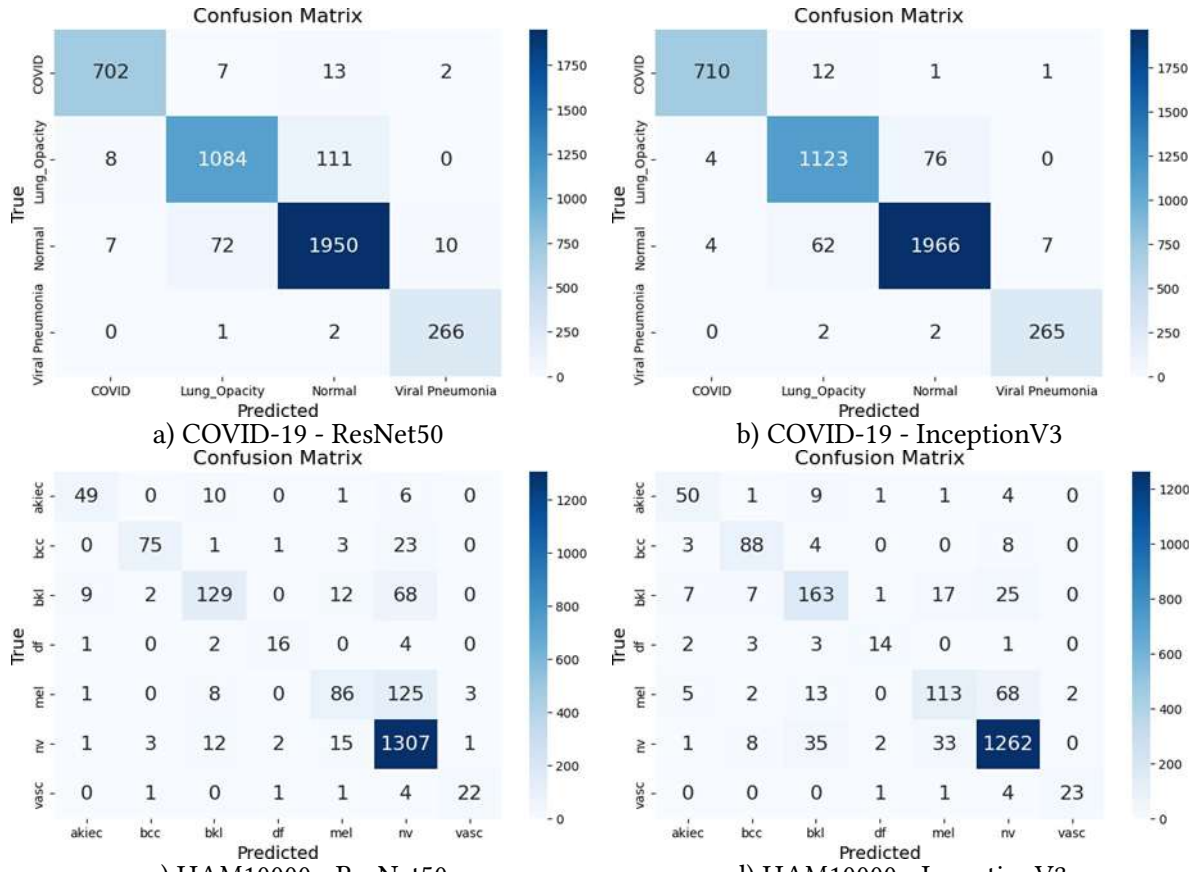
4.2.8. With 40% augmentation

The table 10 presents the performance of the InceptionV3 and ResNet50 models on the COVID-19 Radiography and HAM10000 datasets with a 40% data augmentation using approach 4.

Table 10
Performance results of the InceptionV3 model with approach 4: augmentation by StyleGAN3 and balancing with traditional methods

Model	COVID				HAM10000			
	Acc	F1	Recall	Prec	Acc	F1	Recall	Prec
ResNet50	93.24%	93.21%	93.25%	93.27%	82.94%	81.58%	82.94%	81.93%
InceptionV3	95.18%	95.18%	95.18%	95.19%	85.38%	84.99%	85.39%	84.91%

The results show that InceptionV3 continues to exhibit better performance compared to ResNet50 in terms of accuracy and F1-score. For the COVID-19 dataset, InceptionV3 achieves an accuracy of 95.18%, while ResNet50 shows an accuracy of 93.24%. Regarding the HAM10000 dataset, InceptionV3 achieves an accuracy of 85.38%, compared to 82.94% for ResNet50, confirming the effectiveness of InceptionV3 for this approach.



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 8: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets with approach 4 at 30%.

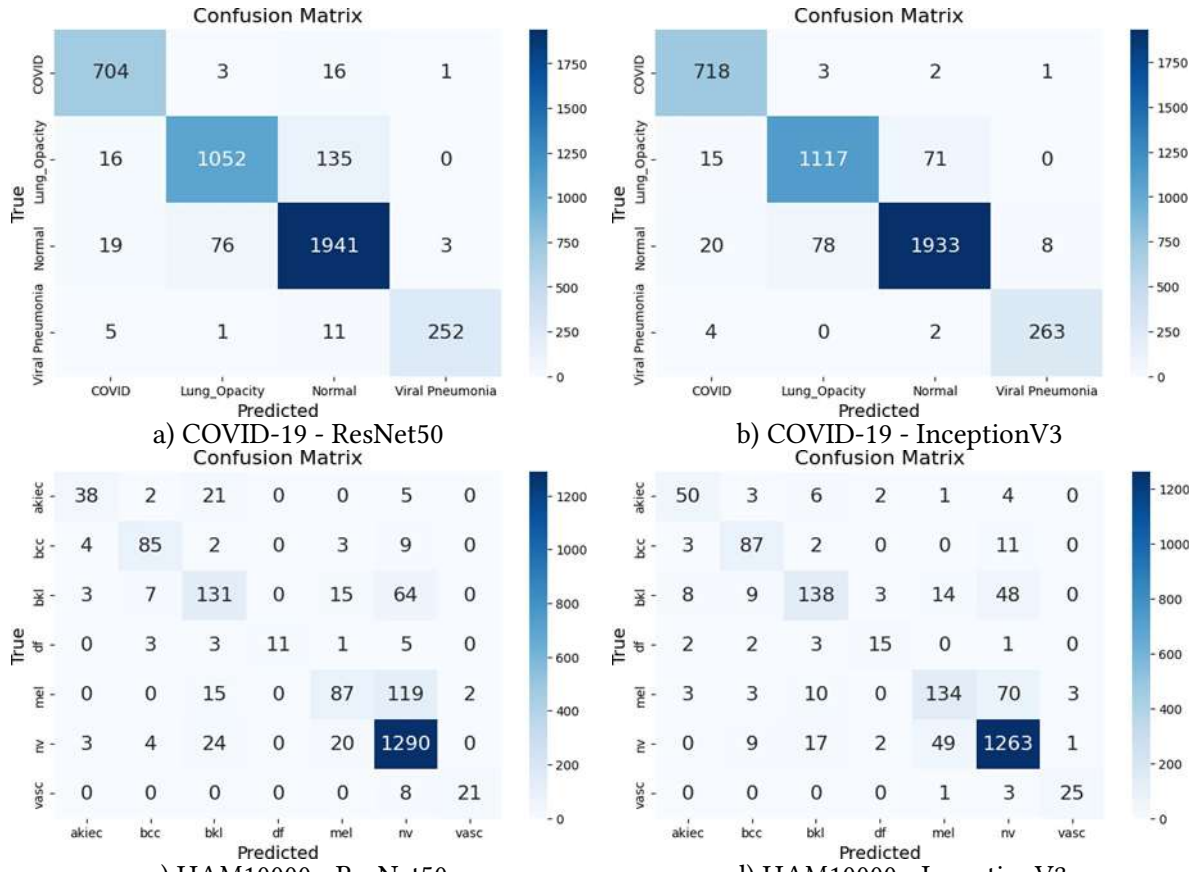
4.3. Discussion and comparison

For the COVID-19 Radiography dataset, approach 4, which includes a 30% increase in generated data, proved to be the most effective. It achieved an accuracy of 95.96% for the InceptionV3 model and 94.49% for ResNet50, outperforming all other tested approaches.

In the HAM10000 dataset, approach 4 also delivered the best results, especially for InceptionV3, which reached an accuracy of 86.43%, surpassing other methods.

Approach 1 relies on traditional data augmentation, but its limitations quickly become apparent. On the COVID-19 Radiography dataset, it allows InceptionV3 to achieve an accuracy of 94.82% and ResNet50 91.26%, while on the HAM10000 dataset, the performances are 83.09% for InceptionV3 and 82.59% for ResNet50. However, this unbalanced approach does not provide significant improvements and may even lead to decreased performance due to the persistent class imbalance. This is where approach 2, which incorporates class balancing along with data augmentation, proves to be more effective. Indeed, on the COVID-19 Radiography dataset, it achieves an accuracy of 95.89% for InceptionV3 and 94.40% for ResNet50, and on HAM10000, the results are also improved, with 86.03% for InceptionV3 and 84.49% for ResNet50. This demonstrates that the addition of class balancing allows for better model generalization, particularly on unbalanced datasets, making approach 2 more effective than approach 1.

In approach 3, although the generated images are of good quality, the main issue lies in the constant variation of the images injected into the batches at each training step. This fluctuation prevents the model from converging effectively, as it cannot adapt well to changing data. The lack of consistency in the batches disrupts the model's learning, limiting overall performance improvements. In comparison, approach 2, which uses static data balancing, offers greater stability and enables the model to converge better, thus explaining its superior results.



a) COVID-19 - ResNet50 b) COVID-19 - InceptionV3

c) HAM10000 - ResNet50 d) HAM10000 - InceptionV3

Figure 9: Confusion matrices for ResNet50 and InceptionV3 on the COVID-19 and HAM10000 datasets with approach 4.

5. Conclusion

Conclusion Data augmentation is key to optimizing the performance of deep learning models in medical imaging, especially in the presence of imbalanced and challenging datasets. In this work, the application of StyleGAN in generating synthetic images was investigated and its impact on the training of classification models evaluated.

Our experiments demonstrated that while the synthetic images generated by StyleGAN are realistic and useful for augmenting datasets, they alone are not sufficient to surpass the performance obtained using traditional data augmentation methods. The diversity and realism of the generated images remain a concern, especially with the complexity and variability of medical images, which are not always well-modeled by generative models.

However, this study shows the potential of GANs for enhancing medical classification datasets. While ResNet50 and InceptionV3 have worked effectively, other architectures and fine-tuning strategies can potentially improve model robustness.

Prospective Pathways To supplement this study, there are numerous paths that can be taken:

- Hybrid methods: Combining GANs with other generation techniques, i.e., variational auto-encoders, would further improve synthetic data quality. Systematic clinical validation: Testing these techniques in actual clinical environments to determine their feasibility.
- Combining imbalance handling techniques: Addressing dataset imbalance by integrating two approaches, such as undersampling the majority classes through pruning while simultaneously oversampling the minority classes, can improve model generalization and mitigate bias.

Table 11
Model performance results across different approaches

		COVID-19 Radiography				HAM10000			
	Model	A	F1	R	P	A	F1	R	P
	Approach 1								
	ResNet50	91.26%	91.20%	91.26%	91.50%	82.59%	81.27%	82.59%	81.48%
	InceptionV3	94.82%	94.84%	94.83%	94.88%	83.09%	82.02%	83.09%	82.49%
	Approach 2								
	ResNet50	94.40%	94.37%	94.40%	94.40%	84.49%	84.49%	83.68%	83.16%
	InceptionV3	95.89%	95.88%	95.89%	95.89%	86.03%	86.03%	85.11%	82.02%
	Approach 3								
	ResNet50	94.33%	94.31%	94.33%	94.33%	83.19%	82.64%	83.19%	82.77%
	InceptionV3	95.46%	95.45%	95.47%	95.48%	86.08%	86.19%	86.08%	86.54%
	Approach 4								
10%	ResNet50	93.76%	93.77%	93.77%	93.78%	85.28%	84.97%	85.29%	84.95%
	InceptionV3	95.37%	95.36%	95.37%	95.36%	86.43%	85.61%	86.43%	85.96%
20%	ResNet50	93.76%	93.75%	93.77%	93.75%	84.88%	84.31%	84.89%	84.22%
	InceptionV3	95.58%	95.60%	95.58%	95.62%	85.73%	85.33%	85.74%	85.65%
30%	ResNet50	94.49%	94.48%	94.50%	94.49%	83.99%	82.51%	83.99%	83.26%
	InceptionV3	95.96%	95.96%	95.96%	95.96%	86.43%	86.20%	86.43%	86.14%
40%	ResNet50	93.24%	93.21%	93.25%	93.27%	82.94%	81.58%	82.94%	81.93%
	InceptionV3	95.18%	95.18%	95.18%	95.19%	85.38%	84.99%	85.39%	84.91%

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Detection of Web Propaganda Patterns by Transformer Neural Networks: Improving Efficiency via Dataset Balancing

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Abstract

In the paper, a proposed approach for improving efficiency of web propaganda patterns detection by transformer neural networks is presented. Approach consists of sequential use of three developed methods: method for dataset balancing, method for fine-tuning individual binary neural network models and method for detecting web propaganda patterns. Compared to existing analogues, the use of proposed approach allowed achieving an efficiency increase of 0.1 by F1 metric when detecting propaganda patterns in web texts using transformer neural networks due to dataset balancing optimization. Analyzing the impact of parameter that determines proportion of texts without web propaganda patterns allows assessing how the models ability to distinguish propaganda patterns from neutral texts and texts with other propaganda patterns. This allows finding the optimal ratio of dataset classes to increase the overall effectiveness for detecting web propaganda patterns. Conducted research has established that the highest results were achieved when forming the training dataset with a percentage of texts without patterns of 30% using the RoBERTa neural network, and was achieved 0.725 by F1 metric. Proposed approach ensures the determination of the optimal ratio between text sets with propaganda patterns and neutral text set, which improving the generalization ability of models and reduce their bias.

Keywords

web propaganda patterns, dataset balancing, BERT, RoBERTa, NLP, transformer neural network

1. Introduction

In the modern information environment, propaganda content plays a significant role in shaping public opinion, political views, and social behavior [1]. Social networks have become a key space for disseminating information, but at the same time they are also a tool for manipulative influence [2]. Algorithmic content distribution, personalized news feeds, and automated recommendation systems contribute to the rapid spread of manipulative messages, which makes it difficult to detect web propaganda patterns using traditional methods [3, 4]. Since manipulative content can have subtle linguistic markers and adapt to the context [5], its identification requires the use of context-oriented language models, in particular transformers [6]. Significant progress in the field of automatic text analysis has made it possible to use neural networks to detect manipulations, but the accuracy of such models largely depends on the training sample. The balance of the sample affects the model's ability to recognize manipulative patterns and distinguish them from neutral or unintentional influence [7].

The research is closely related to the UN Sustainable Development Goals, as it contributes to the formation of quality education (SDG No. 4) through the development of media literacy and critical thinking [8]. This allows society to more effectively recognize manipulative content and make informed decisions, which is consistent with the principles of ensuring access to reliable information. In addition, methods for detecting web propaganda patterns in text messages play an important role in maintaining peace, justice and strengthening democratic institutions (SDG No. 16) [9, 10]. They help combat disinformation, increase the level of transparency of governance and contribute to reducing the impact of manipulation in society, which is a key factor in the sustainable development of the information space [11].

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The aim of paper is to improve the efficiency of detecting propaganda patterns in web texts using transformative neural networks by optimizing the dataset balancing. Research is aimed at reducing the impact of class imbalance, increasing the accuracy of classification and improving the generalization ability of model.

The main paper contribution is created methodology that includes method for fine-tuning individual binary neural network models to detect propaganda patterns, method for balancing the dataset, and method for detecting web propaganda patterns. The paper also provides an analysis of the impact of the balance of the training sample on the effectiveness of models for detecting manipulative patterns in social media. An experimental study of the performance of the BERT and RoBERTa transformative language models depending on the distribution of training examples between classes was conducted. The results obtained contribute to a deeper understanding of the role of the training sample in improving algorithms for detecting manipulative texts and can be used to increase the reliability of automated systems for analyzing the information space.

2. Related Works

The issue of automated detection of web propaganda patterns in social media has widely attracted the attention of researchers.

The research [12] considers a multimodal and multilingual dataset of propaganda patterns PPN (Propagandist Pseudo-News), which contains news texts collected from web resources that expert organizations have classified as containing manipulation patterns. The study analyzes various NLP approaches that allow identifying the characteristic features that annotators have highlighted and comparing them with the results of automated classification. For this purpose, the following methods are used: VAGO to determine the level of subjectivity and vagueness of statements, TF-IDF as a basic analysis tool, as well as four classification algorithms – two RoBERTa models, CATS, which focuses on syntactic features, and XGBoost, which combines semantic and syntactic features.

In [13] two architectures for classifying propaganda patterns were analyzed: one involved the use of data augmentation (EDA) methods, and the other worked without them. The models using EDA showed a 3% improvement in F_1-measure, reaching 57.57% on the test set. A significant increase in accuracy was observed for manipulation patterns such as "Appeal_to_fear-prejudice", "Exaggeration, Minimisation" and "Repetition", while for individual techniques, in particular "Doubt" and "Flag-Waving", a slight decrease in results was noted. "Causal_Oversimplification" and "Thought-terminating_Cliches" showed the most noticeable improvement. Determination of optimal parameters for classification was carried out by analyzing the number of epochs, the length of text fragments and the learning rate. This allowed the authors to achieve an F_1-measure of 44% in the sentiment detection task and 57% in the classification of manipulation patterns.

The authors of [14] used the RoBERTa language model to detect propaganda patterns in news articles. The model was evaluated on the SemEval-2020 Task 11 reference dataset, which confirmed its effectiveness in recognizing complex manipulation patterns in text. Compared to baseline model, RoBERTa achieved an F_1-measure of 60.2%, demonstrating its higher accuracy.

In [15] the multilingual set of propaganda patterns was created by translating the PTC and WANLP corpora, supplemented with SemEval23 data. Three models were proposed: MultiProp-Baseline (an ensemble of GPT-2, mBART and XLM-RoBERTa), MultiProp-ML (meta-learning for languages with minimal data) and MultiProp-Chunk (processing long texts exceeding the token limit). As a result of the experiments, the F_1 score for the Polish language was 62.5%.

The study [16] indicates the ambiguity in the ability of LLMs to recognize propaganda patterns in news texts. Experiments conducted on the annotated SemEval2020 Task 11 corpora demonstrated maximum Recall values of 64.53% and Precision of 81.82%. At the same time, none of the models was able to exceed the baseline F_1 score, which was approximately 50%. The highest achieved F_1 score was only 20%, which is significantly inferior to the baseline and indicates the limitations of generative models in ensuring reproducibility.

In [17] emphasize that most previous studies focused on linguistic features to detect manipulation patterns in texts. Therefore, authors propose the method based on meta-learning that allows for automatic identification of semantic manipulation patterns at sentence level in news materials. For this, multi-task learning is used, aimed at detecting semantic contradictions. Proposed approach combines CRF, BiLSTM and pre-trained language models, which provides an F_1-measure of 61% for multilingual data and 68.8% for monolingual.

The authors of [18] evaluate the possibility of using large language models (LLMs), in particular OpenAI GPT-3.5-turbo, to detect propaganda in news articles. The analysis is based on 18 propaganda techniques identified by Martino et al., and covers materials from Russia Today and the SemEval-2020 Task 11 corpus. Using a specially designed prompt, the model determines the presence of propaganda techniques and classifies articles. Qualitative analysis of results allows us to assess effectiveness of LLMs in this task and optimal prompt parameters.

The application of machine learning models to identify manipulation patterns in text content is considered in the study [19]. Among the analyzed approaches, the Stacking Classifier, which uses feature processing methods, in particular Word2Vec and TF-IDF, demonstrates high adaptability and accuracy. Comparative analysis shows that this model outperforms others, such as Naive Bayes, SVM, KNN, Logistic Regression and Random Forest. The implementation of feature engineering significantly improves the results, which is confirmed by the increase in Accuracy, Precision and F_1-measure.

The study [20] considers the application of machine learning methods to detect types of propaganda in the text content of social networks. The authors used data obtained through the social network API to evaluate the effectiveness of various models. The results of the study showed that neural networks, in particular the LSTM architecture, have high accuracy in this task, reaching 77.15%. It is noted that the further implementation of more modern models, such as BERT, can contribute to even better results in future studies.

Paper [21] proposes an ensemble model for identifying manipulation patterns in texts obtained from memes. The authors consider the use of modern pre-trained language models, as well as optimization methods, in particular data augmentation and combining multiple models. The model evaluation was carried out on the SemEval-2021 Task 6 dataset, and the results showed that proposed approach allows achieving an F_1-micro measure of 60.4% on the test set.

Authors of [22] used a two-stage process to determine the optimal threshold for classifying manipulation patterns to assess the effectiveness of the model. First, experiments were conducted with macrothresholds in the range from 0.1 to 0.9, the threshold with the highest F_1 score was selected, after which microthresholds were added for further optimization. The XLM-RoBERTa models were trained using the Adam optimizer, and early termination was used to prevent overtraining. The Accuracy, Precision, Recall, and F_1-measure metrics were used to assess performance at each stage.

From above reviews of scientific publications, it is clear that the issue of balancing datasets in existing methodologies was considered only from the perspective of creating synthetic samples, and the issue of the influence of the number of texts without manifestations of propaganda patterns was not considered at all. Therefore, our study is relevant and aims to eliminate this drawback by analyzing the influence of the number of texts without propaganda patterns on the effectiveness of transformer models.

The paper aims to determine the optimal ratio between texts with propaganda patterns and neutral texts, which will improve the generalizability of the models and reduce their bias.

3. Methodology

To solve the problem of detecting web propaganda patterns, it is first necessary to fine-tune the neural networks to detect each of the web propaganda patterns. Accordingly, this can be formalized as the problem of training a set of individual binary neural network models *NN*, where each model nn_i corresponds to a certain propaganda pattern p_i from the set of propaganda patterns *P*:

$$P = \{ p_1, p_2, \ldots, p_k \}, \quad (1)$$

where p_i – *i*-th propaganda pattern, k – number of unique propaganda patterns, i=1..k. Within the scope of the study, k=10, and the set *P* acquires the following elements:

- p_1=”*Loaded Language*”;
- p_2=”*Glittering Generalities*”;
- p_3 =”*Euphoria*”;
- p_4=”*Appeal to Fear*”;
- p_5=”*FUD*”;
- p_6=”*Bandwagon*”;
- p_7=”*Thought-Terminating Cliche*”;

- p_8="*Whataboutism*";
- p_9="*Cherry Picking*";
- p_{10}="*Straw Man*".

This set of propaganda patterns is linked to the existing data source presented within the framework of UNLP 2025 [23], dedicated to the competition for detecting manipulative propaganda patterns in the Ukrainian-language media space [24].

Accordingly, {*NN*} will take the form:

$$NN = \{nn_1, nn_2, \ldots, nn_k\}, \quad (2)$$

where nn_i – *i*-th neural network for *i*-th propaganda pattern.

Approach for detection of web propaganda patterns by transformer neural networks consists of sequential use of three developed methods: method for dataset balancing, method for fine-tuning individual binary neural network models and method for detecting web propaganda patterns (Figure 1).

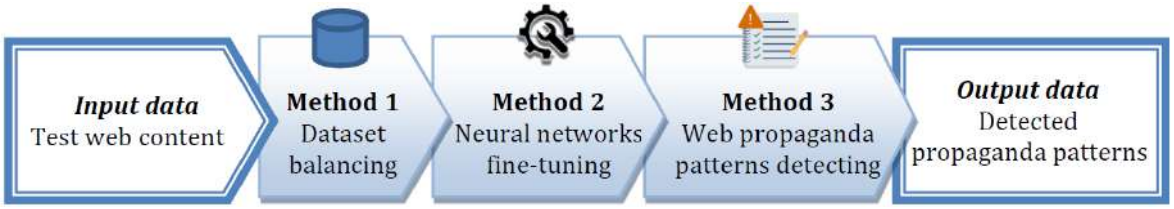

Figure 1: Sequence of methods execution in approach for web propaganda patterns detection

Proposed approach ensures the determination of the optimal ratio between text sets with propaganda patterns and neutral text set, which improving the generalization ability of models and reduce their bias. This improves the efficiency of detecting propaganda patterns in web texts using transformer neural networks through optimizing the dataset balancing.

3.1. Method for Dataset Balancing

Method for dataset balancing is designed to transform the general set of data in the input dataset into 2 datasets (training dataset and validation dataset), which will allow to increase the accuracy of detecting propaganda patterns in web texts. Scheme of training dataset prepare is shown in Figure 2.

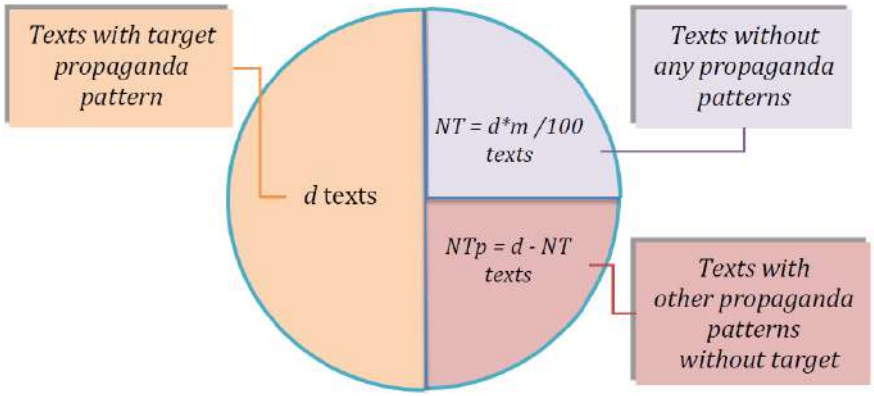

Figure 2: Scheme of training dataset prepare

Percent of texts without manipulation patterns *m* – the studied parameter for analyzing the influence of the balance of the training sample on the effectiveness of models for detecting manipulative propaganda patterns in social media. This parameter has an impact on the formation of the training dataset.

In addition to the training dataset, a validation dataset is constructed, which consists equally of all types of web propaganda patterns and texts without propaganda. This allows determining whether the model does not confuse patterns with each other and whether it is able to detect them independently of each other, which is critically important for the multi-label classification problem.

Accordingly, the result of the method of dataset balancing will be 2 datasets: training dataset and validation dataset. Schematically, their composition is shown in Figure 3.

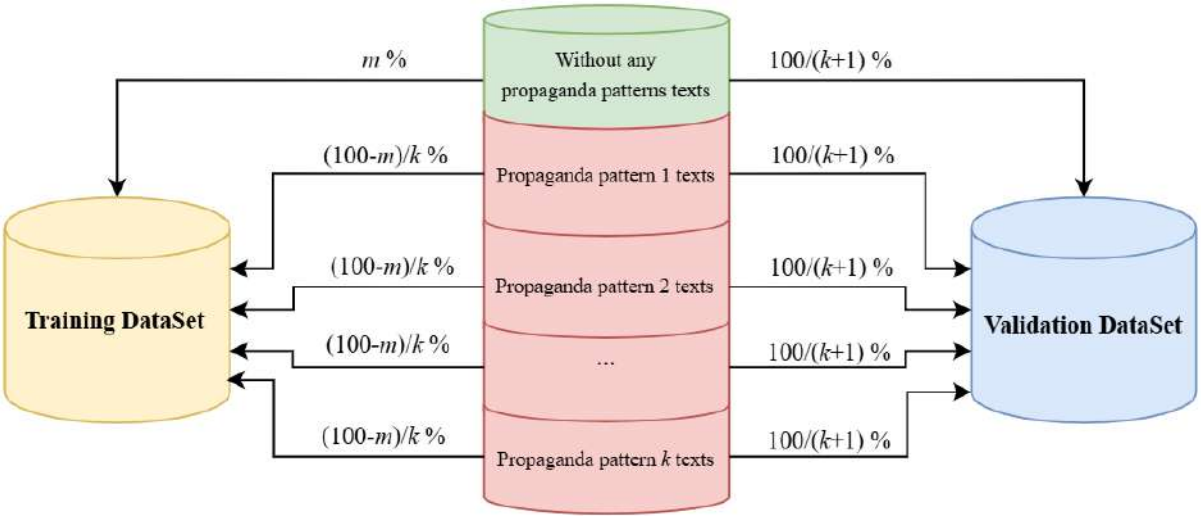

Figure 3: Scheme of datasets balansing for improve accuracy of pattern classification

It is worth noting that the base dataset is annotated at the fragment level, and the training dataset and validation dataset contain not the full text, but fragments (sentences that are marked as propaganda patterns).

The dataset contains annotated data at the fragment level that determine the presence of manipulative influence patterns from the set *P*. A typical text of the dataset from the category "propaganda patterns" can have either one or several labels. A typical text of the dataset from the category "without propaganda patterns" does not contain any web propaganda patterns from the set *P*. According to the marked data, the number of documents corresponding to the patterns $p_1 - p_{10}$ has the distribution shown in Table 1.

Table 1
Distribution of labeled data in dataset by categories (with and without manipulation patterns)

Propaganda patterns	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	without manipulation patterns
Document count	1973	483	462	300	385	157	463	158	512	138	1233

This approach to dataset generation allows us to assess the impact of sample balancing on the quality of propaganda pattern detection, as well as to avoid the dominance of the most common classes in the training set [25]. Using separate binary models for each pattern allows us to model them independently, which is important in problems with class intersection, when one text may contain several types of manipulation. This allows us to investigate how each pattern is separated within the data corpus and how it is affected by the imbalance of the training sample.

3.2. Method for Fine-Tuning Individual Binary Neural Network Model for Propaganda Patterns Detection

As can be seen from Table 1, the data have an uneven distribution, so using a single multi-class neural network model will not allow to obtain high results. A multi-class model tends to dominate widely represented classes, which leads to a decrease in accuracy for poorly represented classes. As a result, the model may simply ignore small categories, which will lead to a significant imbalance in predictions. In addition, multi-class classification assumes that the text belongs to only one class [26], which contradicts the nature of the task, where 1 text can have several labels corresponding to certain web propaganda patterns. Accordingly, using separate binary models for each pi pattern allows to train each model separately without the influence of the imbalance of other classes to take

into account texts with several patterns, since each model from *NN* set works independently and does not limit the choice to only one class.

To investigate the impact of the balance of the training sample on the detection of web propaganda patterns using a set of individual binary neural network models *NN*, it is necessary to first present a method for obtaining a typical individual binary neural network model nn_i for detecting propaganda pattern p_i, the scheme of which is shown in Figure 4.

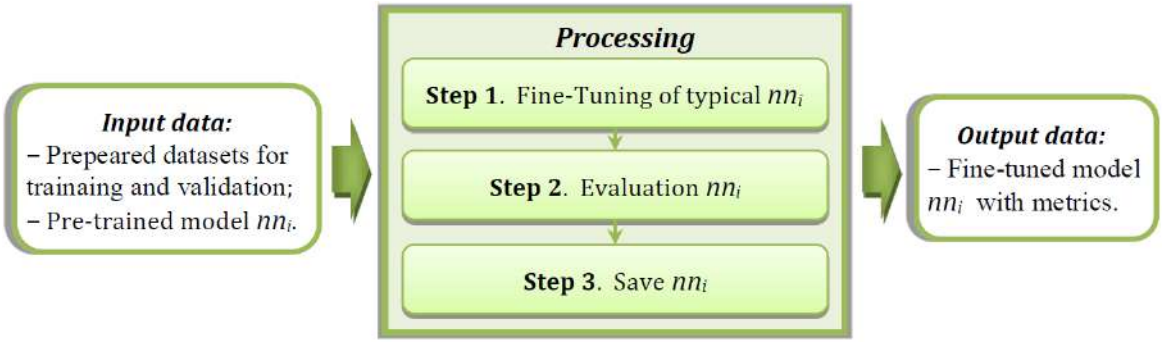

Figure 4: Scheme of method for fine-tuning individual binary neural network model

The input data of the method are prepared datasets for training and validation and pre-trained model *nn*. On Step 1, Fine-Tuning of typical nn_i on training DataSet, formed by method of datasets balancing, is performed. Fine-Tuning within the framework of the study will be carried out for individual binary neural network model BERT [27] and RoBERTa [28] with «HuggingFace» library [29].

Accordingly, on Step 2, evaluation of individual binary neural network model nn_i is performed, for evaluations both training dataset and validation dataset, which were formed by method of datasets balancing, will be used. Evaluation of models will be carried out by metrics Accuracy, Precision, Recall and F_1. On Step 3, save of validated nn_i is performed. Accordingly, output data is fine-tuned model nn_i with metrics.

As pre-trained model *nn*, the use of BERT-like architectures is proposed, since these models can be applied to the analysis of Ukrainian texts even in the absence of large volumes of marked-up data [30, 31]. This feature is associated with pre-training on large text corpora, which allows these models to form universal language representations that can be refined on specific datasets to detect propaganda patterns. Fine-tuning allows you to adapt the model to the specifics of manipulative discourse, in particular in the Ukrainian language environment, which contains both unique stylistic and syntactic features.

3.3. Method for Web Propaganda Patterns Detection

After forming datasets and training a set of individual binary neural network models *NN*, detection of web propaganda patterns occurs. Scheme of method of web propaganda patterns detection by transformer neural networks is shown in Figure 5.

Input data of the method detection of web propaganda patterns by transformer neural networks are fine-tuned models *NN*, web content for analysis and threshold *t*.

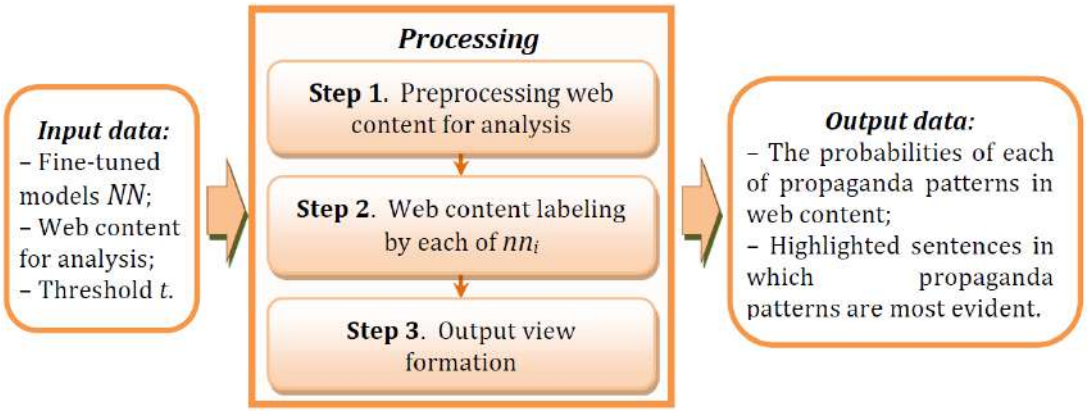

Figure 5: Scheme of method for web propaganda patterns detection

On Step 1, preprocessing of web content for analysis occurs, which includes of splitting into sentences, after which tokenization is performed [32, 33]. The result of web content splitting for analysis will be the representation (3):

$$S=\{s_1,s_2,\ldots,s_n\}, \quad (3)$$

where s_j – j-th sentence in web content for analysis, n – count of sentence.

Step 2 performs web content labeling by each of nn_i. Each sentence s_j is evaluated separately by each of nn_i, and if the output value of the neural network model nn_i for sentence j exceeds the given threshold t –propaganda pattern p_i is considered to be manifested in sentence j. Accordingly, each sentence will be given a subset PP_j of the elements of the set P:

$$PP_j \subseteq P, PP_j=\{p_i | score_{i,j}>t\}, \quad (4)$$

where $score_{i,j}$ – the output value nn_i of the model for j-th sentence in $\{S\}$.

At Step 3, the formation of output view takes place, which is performed according to rules:

- if there are already manifestations of other propaganda patterns for sentence sj, then such propaganda patterns are considered manifested in the text, however, the maximum value max_score_j will be displayed with highlighting:

$$max_¿ = \max_{p_i \subseteq PP_j} score_{i,j}, \quad (5)$$

- if there are multiple sentences with the p_i propaganda pattern, the overall score of the manifestation in web content for analysis is calculated as the arithmetic mean:

$$S\,score=\frac{1}{¿\,SS_i \vee ¿ \sum_{s_j \subseteq SS_i} score_{i,j}, SS_i=\{s_j \vee p_i \in PP_j\}¿} \quad (6)$$

where SS_i – a set of sentences in which p_i is found.

Output data of the proposed method are probabilities of each of propaganda patterns in web content and highlighted sentences in which identified patterns are most evident [34].

The proposed in sections 3.1 – 3.2 methods are investigated experimentally in section 4.

4. Experiment

In accordance with purpose of research, problem of improving efficiency via dataset balancing arises, which can be mathematically represented as a problem of maximizing the F_1 metric:

$$m^¿ = arg\max_m f(m), \quad (7)$$

where $f(m)$ – the value of the F_1 metric of the nn_i model obtained after fine-tuning on the dataset with the selected percentage value m.

The solution of the optimization problem will be carried out experimentally, changing the % of non-propaganda texts in the Training DataSet from 10% to 70% in steps of 20%.

For the experimental part, specialized software was created, consisting of 2 modules: a training module (without a graphical user interface) and a neural network validation module (the application is shown in Figure 6). The Python language, PyTorch libraries [35], transformers [36], datasets [37] were used to develop the training module. The PySide6 libraries [38], transformers, PyTorch were used to develop the validation module.

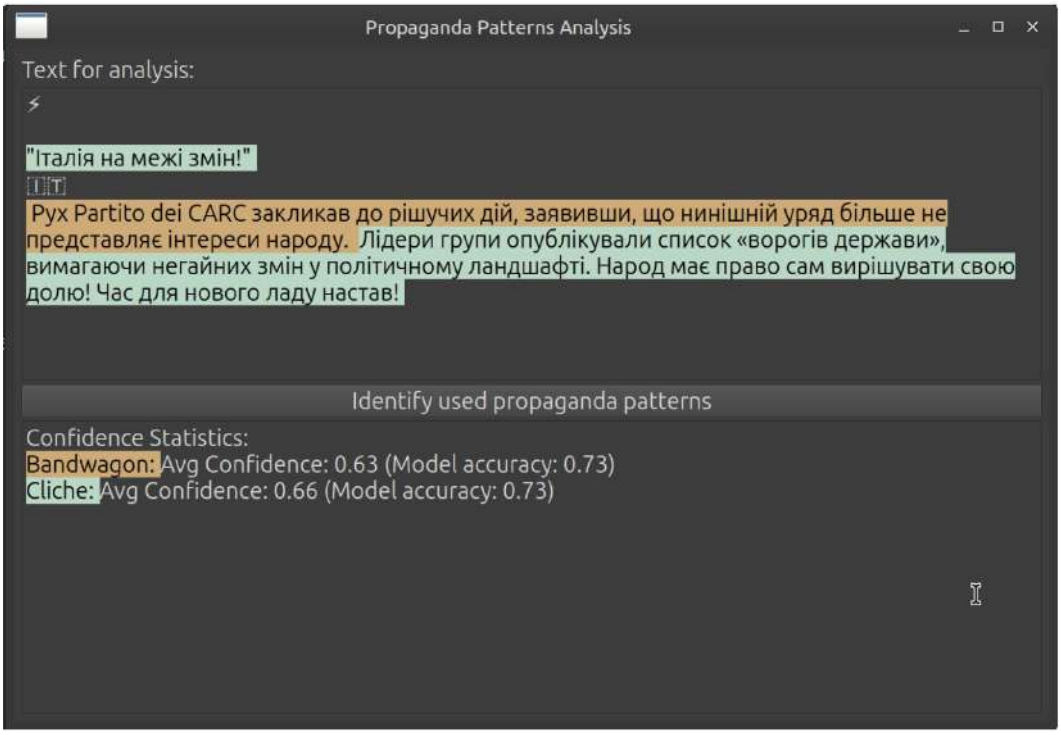

Figure 6: Web propaganda patterns detection by test software

Accordingly, the created test software obtained the results shown in Section 5.

5. Results

After filling the Training DataSet using the method described in section 3.1, data sets were obtained, the quantitative distributions of which are given in Table 2.

Table 2
Distribution of training dataset elements by percentage of texts without propaganda patterns (*m*)

Propa-ganda patterns	Target	Non target	Target	Non target	Target	Non target	Target	Non target
m %	10%		30%		50%		70%	
p_1	695	657	695	668	695	679	695	690
p_2	320	311	320	317	320	314	320	317
p_3	1032	954	1032	982	1032	1012	1032	1026
p_4	767	719	767	740	767	761	767	762
p_5	684	646	684	659	684	667	684	679
p_6	1131	1028	1131	1059	1131	1095	1131	1116
p_7	887	822	887	840	887	868	887	881
p_8	2541	2087	2541	2253	2541	2391	2541	2485
p_9	296	291	296	292	296	293	296	293
p_{10}	321	311	321	317	321	316	321	318

The Precision (P), Recall (R), F_1 metrics for fine-tuned individual binary neural network models at different percentage values of the parameter m on the test sample (20% of the Training DataSet, which did not participate in training) are given in Table 3. The Precision (P), Recall (R), F_1 metrics for fine-tuned individual binary neural network models at different percentage values of the parameter m on the training sample (80% of the Training DataSet, which participated in training) are given in Table 4.

Table 3

Results on test sample (20% of the training dataset that did not take part in training)

		10%			30%			50%			70%		
	Propaganda patterns	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
BERT	p_1	0.5105	0.5205	0.4979	0.6169	0.6173	0.6094	0.7365	0.7224	0.717	0.816	0.8002	0.7976
	p_2	0.7475	0.7456	0.746	0.7165	0.7139	0.7125	0.7668	0.7635	0.7618	0.8346	0.8333	0.8334
	p_3	0.6401	0.6391	0.639	0.6804	0.6803	0.68	0.7125	0.7122	0.7122	0.8096	0.7949	0.7937
	p_4	0.6162	0.6162	0.6162	0.6487	0.6484	0.6485	0.7165	0.7164	0.7161	0.8284	0.8159	0.8154
	p_5	0.6342	0.6343	0.6337	0.6969	0.6963	0.6947	0.7402	0.7332	0.7321	0.8431	0.8378	0.8374
	p_6	0.6655	0.6535	0.6555	0.6408	0.6406	0.6405	0.7718	0.7717	0.7713	0.8400	0.8359	0.8354
	p_7	0.5446	0.5436	0.5439	0.6609	0.649	0.6431	0.6941	0.6830	0.6804	0.7886	0.7810	0.7803
	p_8	0.5867	0.5591	0.5615	0.6878	0.6875	0.6875	0.7232	0.7109	0.7069	0.812	0.8047	0.806
	p_9	0.5839	0.5829	0.5686	0.6575	0.6501	0.6469	0.7314	0.7139	0.708	0.8305	0.8277	0.8269
	p_{10}	0.6241	0.6271	0.6227	0.6010	0.6017	0.6013	0.685	0.6864	0.6845	0.7819	0.7797	0.7771
RoBERTa	p_1	0.5184	0.527	0.5057	0.6056	0.6069	0.5993	0.7096	0.7052	0.7028	0.8067	0.7952	0.7932
	p_2	0.7403	0.7368	0.7373	0.7372	0.737	0.7368	0.7543	0.7521	0.7522	0.8578	0.8559	0.8560
	p_3	0.6506	0.6504	0.6504	0.6919	0.6914	0.6914	0.7096	0.7085	0.7083	0.8303	0.8168	0.8160
	p_4	0.5888	0.583	0.583	0.6571	0.652	0.652	0.6981	0.6982	0.6981	0.8014	0.8014	0.8014
	p_5	0.6527	0.6528	0.6527	0.6952	0.6941	0.6943	0.7455	0.7422	0.7418	0.8289	0.8289	0.8289
	p_6	0.6038	0.5984	0.6002	0.6564	0.6563	0.6562	0.732	0.7244	0.7203	0.7972	0.7969	0.7968
	p_7	0.5062	0.5067	0.5064	0.6027	0.6026	0.6025	0.6384	0.6373	0.6373	0.7489	0.7484	0.7484
	p_8	0.6071	0.5748	0.5764	0.7344	0.7344	0.7344	0.7591	0.7500	0.7478	0.7765	0.7500	0.7515
	p_9	0.5819	0.5829	0.5744	0.6035	0.603	0.6029	0.7323	0.7262	0.7241	0.8009	0.8010	0.8009
	p_{10}	0.5889	0.5847	0.5858	0.634	0.6356	0.6344	0.7284	0.7288	0.7267	0.7878	0.7881	0.7874

Table 4

Results of fine-tuned individual binary neural network models on the training set

		10%			30%			50%			70%		
	Propaganda patterns	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
BERT	p_1	0.7419	0.7188	0.7027	0.7854	0.7671	0.7608	0.8228	0.7954	0.7897	0.8986	0.8841	0.8829
	p_2	0.872	0.872	0.8719	0.9127	0.9095	0.9092	0.9228	0.9209	0.9208	0.9461	0.9441	0.9441
	p_3	0.8712	0.8712	0.8712	0.8577	0.8575	0.8576	0.9184	0.9167	0.9165	0.9266	0.922	0.9217
	p_4	0.8957	0.8945	0.8944	0.894	0.8927	0.8925	0.914	0.9099	0.9097	0.9059	0.8935	0.8925
	p_5	0.8694	0.8691	0.8689	0.8763	0.8704	0.8696	0.9103	0.9034	0.9028	0.9318	0.9254	0.9251
	p_6	0.8544	0.8532	0.8533	0.9048	0.9037	0.9037	0.8859	0.8797	0.879	0.9161	0.9096	0.9092
	p_7	0.7846	0.7837	0.7832	0.7877	0.7676	0.7624	0.854	0.8363	0.834	0.9164	0.9101	0.9096
	p_8	0.8694	0.8693	0.8693	0.9235	0.9235	0.9235	0.9455	0.943	0.9429	0.9234	0.9198	0.9197
	p_9	0.7297	0.7084	0.6988	0.7742	0.766	0.7631	0.852	0.8306	0.8277	0.8968	0.8809	0.8798
	p_{10}	0.6622	0.6503	0.6452	0.9114	0.9106	0.9106	0.8301	0.8301	0.8301	0.8886	0.8811	0.8807
RoBERTa	p_1	0.752	0.7358	0.7246	0.8103	0.7867	0.7801	0.8455	0.8289	0.826	0.9076	0.896	0.8951
	p_2	0.8851	0.8844	0.8843	0.9156	0.9146	0.9144	0.9532	0.953	0.953	0.9568	0.9562	0.9561
	p_3	0.908	0.9079	0.9079	0.9424	0.9413	0.9413	0.9409	0.938	0.9378	0.9484	0.945	0.9448
	p_4	0.9123	0.9121	0.9121	0.9358	0.9358	0.9358	0.9418	0.9399	0.9399	0.9572	0.9549	0.9548
	p_5	0.8948	0.8935	0.8932	0.9006	0.8995	0.8994	0.9277	0.923	0.9227	0.9547	0.9533	0.9532
	p_6	0.8853	0.8849	0.8847	0.9039	0.9037	0.9037	0.9546	0.9546	0.9546	0.9591	0.9568	0.9567
	p_7	0.8232	0.8207	0.82	0.8563	0.8556	0.8554	0.8878	0.883	0.8825	0.9299	0.9272	0.9271
	p_8	0.9287	0.9287	0.9287	0.9414	0.9412	0.9412	0.9485	0.947	0.9469	0.9591	0.9589	0.9589
	p_9	0.8409	0.8312	0.8294	0.8736	0.8721	0.8718	0.8895	0.8789	0.8779	0.92	0.9149	0.9147
	p_{10}	0.8863	0.8806	0.8803	0.9084	0.9064	0.9063	0.9286	0.9278	0.9278	0.9503	0.949	0.949

The Precision (P), Recall (R), and F_1 metrics for fine-tuned individual binary neural network models at different percentage values of parameter *m* on validation dataset are given in Table 5.

Table 5
Results of fine-tuned individual binary neural network models on the validation dataset

		10%			30%			50%			70%		
	Propaganda patterns	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
BERT	p_1	0.6686	0.6529	0.6283	0.6623	0.6457	0.6184	0.6689	0.6279	0.577	0.7046	0.6247	0.5551
	p_2	0.7828	0.778	0.7764	0.7901	0.7641	0.7571	0.7744	0.7362	0.7244	0.7802	0.7339	0.7199
	p_3	0.7582	0.7551	0.7536	0.7403	0.7362	0.7342	0.7506	0.7189	0.7072	0.7209	0.6292	0.579
	p_4	0.737	0.7202	0.7133	0.7412	0.7239	0.7171	0.7095	0.658	0.6309	0.7094	0.6025	0.5355
	p_5	0.7462	0.7384	0.734	0.7533	0.7296	0.7191	0.7536	0.7043	0.6829	0.7434	0.6525	0.6054
	p_6	0.7135	0.7046	0.7009	0.7485	0.7283	0.7219	0.7178	0.6714	0.6514	0.7167	0.6209	0.5709
	p_7	0.6523	0.6473	0.6415	0.6646	0.6291	0.6009	0.671	0.615	0.5715	0.6934	0.6109	0.5546
	p_8	0.7204	0.7172	0.7158	0.7518	0.7314	0.725	0.7575	0.6888	0.6647	0.703	0.6414	0.6091
	p_9	0.6531	0.6286	0.6074	0.6691	0.6485	0.6333	0.6941	0.6246	0.5802	0.704	0.6071	0.5451
	p_{10}	0.6284	0.6207	0.6122	0.7282	0.7069	0.6983	0.684	0.6724	0.6654	0.6872	0.619	0.5755
RoBERTa	p_1	0.6771	0.6639	0.644	0.6843	0.6607	0.6332	0.6872	0.6544	0.6197	0.7123	0.6366	0.5755
	p_2	0.8057	0.8013	0.8	0.8001	0.7844	0.7805	0.7965	0.7757	0.7704	0.7897	0.7472	0.7354
	p_3	0.7738	0.7649	0.7619	0.7861	0.7611	0.7542	0.7569	0.7091	0.6917	0.764	0.6692	0.6313
	p_4	0.755	0.7506	0.7487	0.7859	0.7779	0.7756	0.752	0.7121	0.6975	0.7663	0.7032	0.6811
	p_5	0.781	0.7721	0.7684	0.7587	0.745	0.7387	0.7793	0.7394	0.7253	0.7624	0.7048	0.6811
	p_6	0.741	0.7267	0.722	0.7632	0.752	0.7489	0.7648	0.7441	0.7384	0.7467	0.6635	0.6307
	p_7	0.6669	0.6568	0.648	0.6732	0.6588	0.6477	0.6651	0.6278	0.5982	0.6895	0.6278	0.5867
	p_8	0.7539	0.7488	0.7472	0.7851	0.7694	0.7656	0.7796	0.7235	0.7076	0.749	0.7172	0.7068
	p_9	0.7156	0.688	0.6745	0.7092	0.6905	0.6807	0.7281	0.6695	0.6421	0.7121	0.644	0.6069
	p_{10}	0.7261	0.7069	0.699	0.7516	0.7293	0.7219	0.7386	0.6948	0.6778	0.736	0.6672	0.6378

Comparisons by the Accuracy metric (average value) for fine-tuned individual binary neural network models of the BERT and RoBERTa architectures at different percentage values of the parameter *m* on the Validation DataSet are shown in Figure 7.

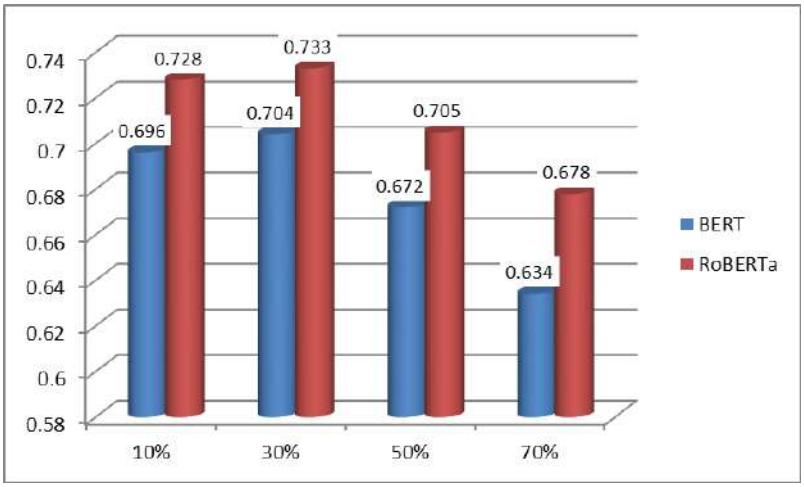

Figure 7: Comparison of fine-tuned models on validation dataset by Accuracy metric

Comparisons by F_1 metric (average value) for fine-tuned individual binary neural network models of the BERT and RoBERTa architectures at different percentage values of the parameter *m* on the Validation DataSet are shown in Figure 8.

It is also worth providing a table comparing the obtained results with the data of existing studies (Table 6).

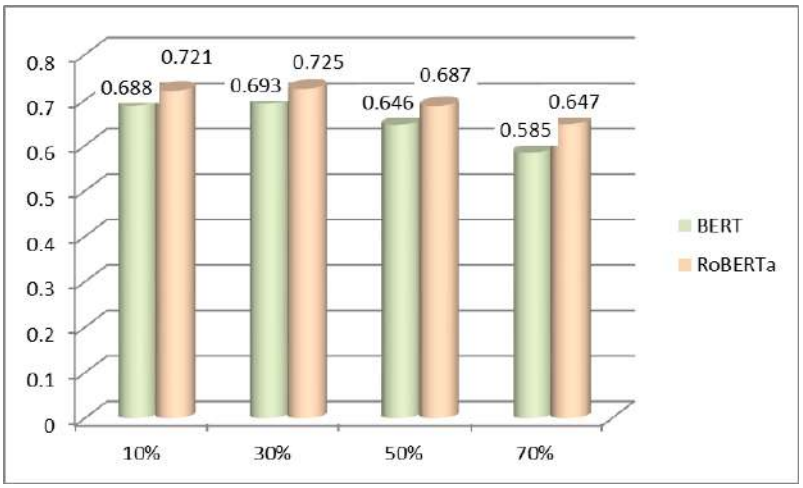

Figure 8: Comparison of fine-tuned models on validation dataset by F_1 metric

Table 6
Comparison of obtained results with existing research

Way of obtaining the result	Language	F_1
BERT, *m=10%*	Ukrainian	0.688
BERT, *m=30%*	Ukrainian	0.693
BERT, *m=50%*	Ukrainian	0.646
BERT, *m=70%*	Ukrainian	0.585
RoBERTa, *m=10%*	Ukrainian	0.721
RoBERTa, *m=30%*	Ukrainian	0.725
RoBERTa, *m=50%*	Ukrainian	0.687
RoBERTa, *m=70%*	Ukrainian	0.647
CRF+ BiLSTM [17]	multilingual	0.61
MultiProp-Baseline En-B [15]	Polish	0.625
RoBERTa [14]	English	0.602
Ensemble model [21]	English	0.604
Base + EDA [13]	not indicated	0.576

Therefore, the problem of improving efficiency via dataset balancing, given in the form (7), has a solution $m^* = 30$. An analysis of the obtained results is given in Section 6.

6. Discusion

In the presented results of testing models (Table 3) for detecting manipulative propaganda patterns on the test sample (20% of the training sample) with different percentages of texts without manipulations m (10%, 30%, 50%, 70%), one can observe a clear trend towards improving the performance of models with an increase in the value of the parameter m, i.e. with an increase in the percentage of texts without propaganda patterns in the training sample. For fine-tuned models based on BERT, it is seen that Precision, Recall and F_1-measure for each category of propaganda patterns gradually increase from m=10% to m=70%. For example, for the "Loaded Language" category, the F_1-measure increases from 0.498 at m = 10% to about 0.798 at m = 70%, which indicates a significant improvement in the model's ability to distinguish target and non-target examples with an increase in the proportion of text samples without manipulations.

Comparing the performance of models for different propaganda patterns shows that some categories, such as "Glittering Generalities" and "Bandwagon", "Cherry Picking", have consistently high F_1-measures as m increases, indicating that the characteristic features of these patterns are easier to separate with balanced training. In contrast, other categories, such as "Straw Man" and

“Thought-Terminating Cliche”, show relatively lower performance, which may be due to greater variability or subtlety of the linguistic features characterizing these patterns.

Similar analysis for RoBERTa-based models shows similar trends, with the overall performance being slightly higher compared to BERT models. This is explained by the more robust pre-training and optimized architecture of RoBERTa, which allows the model to generalize information better. The improvement in the evaluation indicators with an increase in the proportion of unmanipulated text samples highlights the importance of balancing the dataset to overcome the problem of class imbalance, which, in turn, contributes to more reliable and stable detection of propaganda patterns by individual binary neural networks. For the BERT neural network, on average, for the F_1 metric, the delta between m = 10% and m = 30% is +0.048, between m = 30% and m = 50%, the delta is 0.063, and between m = 50% and m = 70%, the delta is 0.091. At the same time, for the RoBERTa neural network, delta of +0.0632 is observed between m = 10% and m = 30%, a delta of 0.056 is observed between m = 30% and m = 50%, and delta of 0.082 is observed between m = 50% and m = 70%.

The analysis of the data from Table 4 indicates the ability of neural network models to remember, and here, naturally, as in Table 3, there is a tendency for metrics to increase with increasing parameter m. For the BERT neural network, on average, for the F_1 metric, there is a delta between m = 10% and m = 30% of +0.049, between m = 30% and m = 50%, there is delta of 0.02, and between m = 50% and m = 70%, there is delta of 0.031. At the same time, for the RoBERTa neural network, a delta of +0.028 is observed between m = 10% and m = 30%, delta of 0.022 is observed between m = 30% and m = 50%, and delta of 0.024 is observed between m = 50% and m = 70%. Accordingly, RoBERTa demonstrates a gradual increase in metrics, which indicates stable generalization due to the optimized architecture. BERT demonstrates somewhat jumpy increases, which may be due to the lower flexibility of its architecture in adapting to changes in the proportion of text samples without propaganda patterns.

For the RoBERTa neural network, when detecting manipulation patterns “Glittering Generalities”, “Appeal to Fear”, “FUD”, “Bandwagon”, “Whataboutism”, an F_1 value of more than 0.95 is observed. For the BERT neural network, a value above 0.95 is observed only for “FUD”. In general, the use of different values of the parameter m affects the ability of neural networks to remember the features of the training set. However, the metrics calculated on the training data allow us to assess how well the model remembered this data, but do not give a complete picture of its ability to generalize new information.

The most relevant estimates of the experiment are given in Table 5, since here the model was validated on data that did not participate in training, and which contain equally represented propaganda patterns and texts without such patterns.

According to Table 5 and Figures 7 and 8, at the parameter m=30% the metrics demonstrate the highest result, where the average value of the Accuracy metric is 0.733 for the RoBERTa neural network, and 0.704 for the BERT architecture. The F_1 metric for RoBERTa is 0.725, and for the BERT architecture – 0.693. This suggests that the initial addition of data allows to increase the metrics, but then the effect is smoothed out or even worsened due to overloading with less useful information, such as texts without propaganda patterns. Accordingly, while neural networks show a tendency to better distinguish propaganda patterns at higher values of m during training, testing on a balanced validation set refutes the hypothesis that the higher the resolution of the training data, the better the generalization ability of the neural network model. It is possible that as the proportion of m increases, the models are overtrained due to the lack of unique values inherent in each of the web propaganda patterns. The conclusion that the m^*=30 found is also confirmed by the minimum mean deviation between the test data for m=30 (Table 3 and Table 5) for both the BERT architecture neural network (0.05) and RoBERTa (0.06).

The comparison with analogues is carried out in Table 6, and for the purity of the comparison of the developed approach and existing analogues, the F_1 value was taken specifically on the validation data. Accordingly, the highest F_1 indicator for the RoBERTa architecture at m=30% is 0.725, which is 0.1 higher than the analogue described in [15]. Therefore, the task of improving the efficiency of detecting propaganda patterns in web texts using transformative neural networks through optimizing the balancing of the dataset has been fully implemented and experimentally proven.

However, the proposed approach has limitations. In this study, an approach at the sentence level was used. This may have an impact on the quality of detecting propaganda patterns, which may work at the level of paragraphs or even entire texts, rather than individual sentences. Also, a single sentence may be neutral in itself, but in the context of propaganda text its meaning changes. These issues will be addressed in further research. There are also limitations at the level of the data source.

The manual labeling used in the dataset may contain subjective judgments, which affects the training of the model.

Conclusions

In the paper, a proposed approach for improving efficiency of web propaganda patterns detection by transformer neural networks is presented. Approach consists of sequential use of three developed methods: method for dataset balancing, method for fine-tuning individual binary neural network models and method for detecting web propaganda patterns. Compared to existing analogues, the use of proposed approach allowed achieving an efficiency increase of 0.1 by F_1 metric when detecting propaganda patterns in web texts using transformer neural networks due to dataset balancing optimization.

In addition to the training dataset, consisting of texts with target propaganda pattern in the target category, as well as texts without any propaganda patterns and texts with other propaganda patterns, without target, a validation dataset was built, which consists equally of all types of web propaganda patterns and texts without propaganda. This allows us to determine whether the model does not confuse patterns with each other and is able to detect them independently of each other, which is critically important for the patterns detection task.

An analysis of the impact of the balance of the training sample on the effectiveness of propaganda pattern detection models in social media was performed, which showed that of the considered options for forming the training dataset with different percentages of texts without manipulations (10%, 30%, 50% and 70%), the highest results were achieved at 30% using the RoBERTa neural network, and are 0.725 according to the F_1 metric. The results obtained contribute to a deeper understanding of the role of training sample balancing in improving propaganda pattern detection algorithms and can be used to increase the reliability of automated information space analysis systems.

Building a validation dataset that contains an equal number of texts with all types of propaganda patterns, as well as neutral texts, provides a fair assessment of the performance of the models. This prevents bias towards the most represented classes and allows for more accurate performance metrics for each individual pattern. In addition, this approach allows for the identification of potential relationships between different types of manipulation, since texts can contain multiple patterns at the same time.

Analyzing the impact of parameter that determines proportion of texts without web propaganda patterns allows assessing how the models ability to distinguish propaganda patterns from neutral texts and texts with other propaganda patterns. This allows finding the optimal ratio of dataset classes to increase the overall effectiveness for detecting web propaganda patterns.

The proposed approach has the limitation of analyzing at the sentence level, which may not take into account the broader context of propaganda patterns at the paragraph or whole text level. In addition, the use of manual data labeling may contain subjective judgments, which affects the training of the model.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Developing an Intelligent Geometric Modelling Framework for the Optimization in the Process of Additive Manufacturing

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Abstract

The focus of this research is the creation of intelligent geometric design technologies. The system employs state-of-the-art methods and tools to automate the arrangement and enhance the placement of 3D shapes. Specifically, the aim is to resolve practical issues in optimizing additive manufacturing processes. This is accomplished by merging artificial intelligence techniques with novel computational solutions for superior results. The article presents a nonlinear optimization approach for solving 3D irregular packing problems with arbitrarily moved and rotated objects. Phi-functions and quasi-Phi-functions are used to describe interactions between the 3D objects. The following formulation presents the packing problem in mathematical terms, along with an analysis of its features. A local optimization algorithm is introduced to identify solutions, with a focus on the characteristics that have been delineated. The results of computational experiments suggest that the proposed solution method is effective for 3D irregular packing optimization.

Keywords

Intelligent system, additive manufacturing, phi-function, mathematical modelling, 3D irregular packing problem, local optimization, non-linear optimization

1. Introduction

This paper proposes the development of intelligent geometric design technologies that leverage advanced methodologies and tools to automate and optimize the placement of geometric objects in space. These technologies address applied challenges in optimizing additive manufacturing by integrating artificial intelligence (AI) and innovative computational approaches to achieve optimal solutions.

Three-dimensional packing problems are a useful model for studying well-established optimization scenarios frequently encountered in various engineering disciplines. There is considerable current momentum towards discovering efficient strategies for tackling these problems. These problems find relevance across various real-world scenarios, including the efficient placement of geometric objects, defined by their shape, within constrained spaces. Frequently, the resolution of a 3D packing challenge entails determining the placement of all provided objects within containers of minimal size.

Packing dilemmas constitute essential elements of mathematical and computational modelling. These problems are inherently challenging due to their intricate interplay with optimization, geometric configuration, and space utilization. These challenges catalyze innovation in the field, particularly in algorithms and computational methodologies. These innovations are vital for

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providing solutions to sophisticated real-world problems in the domains of engineering and science. The advancement and refinement of methodologies for addressing these problems are paramount to the continuous development of natural and information-based systems.

Packing problems are prevalent across many scientific and engineering fields. Often, real-world tests are substituted with computer-based modelling, which greatly minimizes time, physical materials, and overall expenses. Take, for instance, reference [1]; this work explores the most effective ways of arranging objects, which can be turned any which way inside a space that has limits. This study highlights noteworthy enhancements in the effectiveness of packing and the smart use of available resources. Progress in the field has been accelerated by improvements in information technology, specifically when studying particles that vary in size (as is seen in [2]). Reference [3] presents a technique that relies on reinforcement learning; it's used to pack odd 3D shapes into a storage area. This method considers physics and the turning of the shapes to assist. A key feature of this technique is lessening the requirements for learning via the creation of likely moves that aid in training. To elaborate, [4] presents a solver based on learning, focusing on packing objects of any shape.

Applications are numerous and span various domains, including biology, geology, medicine, nanotechnology, robotics, and pattern recognition. These implementations also benefit control systems, vehicle construction, chemistry, power and mechanical engineering, and shipbuilding.

The inherent complexity of packing problems, classified as NP-complete, has spurred the exploration of approximation methods. These methods frequently exhibit a heuristic character. The repertoire includes sophisticated search rules [3,4], the principles of genetic algorithms [5], algorithms inspired by ant and bee behaviors, and simulated annealing [6]. Mathematical programming methods [7,8] and their hybrid or integrated variants [9] constitute further solution approaches.

According to reference [4], the progression of a standard solution algorithm is typically characterized by three repeating phases. The initial phase involves the selection of an order for the objects. The subsequent phase entails the positioning of the objects based on the selected order. The final phase concerns the computation of the objective function's value. It should be noted, however, that the positioning of these objects is subject to several variations, primarily distinguished by the following elements: the trajectory the objects take, the rotation constraints applied, and whether the process tolerates or actively prevents overlap.

Many publications impose restrictions on the rotation of three-dimensional objects, limiting them to specific angles, such as 45 or 90 degrees, or completely prohibiting alterations to an object's orientation. For instance, reference [11] utilizes elementary translational movement to arrange convex polytopes. Lamas-Fernandez et al. (2023) have also developed voxel-based approaches to address the 3D irregular packing problem [13]. The research in [12] introduces the HAPE3D algorithm, which focuses on packing polyhedra with rotations limited to eight predetermined angles around the coordinate axes. Finally, the study documented in [14] concludes that determining object orientations across a full 360-degree range in 3D is not a practical solution.

In the face of the daunting task of developing meaningful mathematical models, formulating equivalent expressions for continuous rotations of three-dimensional geometric figures is a pursuit by a select few researchers. In this context, techniques for ellipsoid packing are examined, leveraging both continuous and differentiable nonlinear optimization strategies, as demonstrated in [15, 16]. Packaging multiple convex 3D objects is the primary subject of discussion in reference [17].

This research is devoted to developing an intelligent system that will optimize the 3D printing process of many industrial parts using unique intellectual tools and technologies for modelling and solving optimization problems of geometric design. The proposed approach involves modelling and solving the optimization problem of packing non-convex geometric objects.

To this end, a multifaceted approach is employed, integrating mathematical and computer simulation methodologies. These methodologies are meticulously designed to accurately capture the interactions (non-intersection conditions) between geometric objects. This strategy enables formulating the primary problem as a nonlinear optimization problem. The mathematical underpinnings of our methodology are rooted in the phi-functions method, exhaustively delineated in [17]. This method provides a rigorous analytical representation of both the constraints that prevent intersection and the constraints that ensure the location of objects in the container. A critical aspect of our methodology is the incorporation of continuous rotational transformations

and parallel translational motions of objects, ensuring a comprehensive and precise representation of the geometric constraints.

The primary goal of this research is to develop an intelligent geometric design system that enhances the automation and optimization of 3d shape arrangement, particularly for additive manufacturing (3d printing) applications. The work seeks to improve packing efficiency by integrating artificial intelligence (AI) with advanced computational geometry techniques.

This research advances the field of intelligent geometric design by introducing a novel optimization framework for 3d irregular packing. Combining AI techniques with computational geometry provides a viable additive manufacturing solution, demonstrating theoretical innovation and industrial applicability. The computational experiments confirm the method's effectiveness, paving the way for smarter, more efficient manufacturing processes.

2. Problem definition

The proposed intellectual system is predicated on a distinctive universal mathematical model of optimization geometric design, constructed with specialized intellectual means of modelling this category of problems. These intellectual means encompass specific functions designated as "phi-functions" [18]. These functions facilitate the construction of a generalized universal mathematical model in the form of a nonlinear optimization problem.

Let there be the following convex geometric objects:

- a convex polyhedron J_1 given by vertices $p_{1t}=(p_{1t}^1, p_{1t}^2, p_{1t}^3), t \in T_1=\{1,2,\dots,\varrho_1\};$.
- a circular cylinder $J_2=\{X \in \mathbb{R}^3, x^2+y^2-R_2^2 \le 0, 0 \le z \le H_2\};$
- a sphere $J_3=\{X \in \mathbb{R}^3, x^2+y^2+z^2-R_3^2 \le 0\};$
- a circular cone $J_4=\{X \in \mathbb{R}^3, x^2+y^2-c_4^2(z-E_4)^2 \le 0, z \ge 0, E_4>0\};$
- a truncated circular cone $J_5=\{X \in \mathbb{R}^3, x^2+y^2-c_5^2(z-E_5)^2 \le 0, E_5 \ge H_5 \ge 0, 0 \le z \le H_5\};$
- a spherical segment $J_6=\{X \in \mathbb{R}^3, x^2+y^2+(z+H_6)^2-R_6^2 \le 0, z-H_6 \le 0, 0<H_6<R_6\};$
- a half-space $J_7=\{X \in \mathbb{R}^3, z \le 0\}$.

We suppose that each concave geometric objects Q_i, $i \in I=\{1,2,\dots,n\}$, is a finite union of convex geometric objects $O_i=\bigcup_{k=1}^{\kappa_i} O_{ik}$ where O_{ik} are geometric objects of kind J_r, $r=1,2,\dots,7$. The location of each object O_{ik} with respect to the local coordinate system of O_i is given with placement parameters $u_{ik}=(v_{ik}, \theta_{ik})$, $k \in K_i=\{1,2,\dots,\kappa_i\}$.

A container C can be a rectangular parallelepiped (rectangular prism or cuboid) $\mathbb{C}_1=\{X \in \mathbb{R}^3, w_1 \le x \le w_2, l_1 \le x \le l_2, \eta_1 \le x \le \eta_2\}$, where $w_1 \ge 0$, $l_1 \ge 0, \eta_1 \ge 0$,or a right circular cylinder $\mathbb{C}_2$ with height $h=h_2-h_1$ $(h_2 \ge h_1)$ and radius r, or a solid sphere $\mathbb{C}_3=\{X \in \mathbb{R}^3, x^2+y^2+z^2-R^2 \le 0.$

Basic problem. Pack geometric objects O_j, $i \in I$, without their mutual overlapping in the container C so that its volume will reach the minimum value.

We assume

$$\hbar=\begin{cases}(w_1,w_2,l_1,l_2,\eta_1,\eta_2) \in \mathbb{R}^6 \, if \, \mathbb{C}=\mathbb{C}_1,\\ (r,h) \in \mathbb{R}^2 \, if \, \mathbb{C}=\mathbb{C}_2,\\ r \in \mathbb{R}^1 \, if \, \mathbb{C}=\mathbb{C}_3.\end{cases}$$

Geometric objects O_i (in what follows objects) both are allowed to be translated by a vector $v_i=(x_i, y_i, z_i)$ and to rotate by angles $\theta_i=(\varphi_i, \psi_i, \omega_i)$. Hence, a vector $u_i=(v_i, \theta_i)=(x_i, y_i, z_i, \varphi_i, \psi_i, \omega_i)$ gives a location of O_i in $\mathbb{R}^3$. Thus, the vector $u=(u_1, u_2, \dots, u_n) \in \mathbb{R}^{6n}$ gives the location of all O_i, $i \in I$, in $\mathbb{R}^3$.

Then, components of the vector $(u,ħ)=(u_1,u_2,\dots,u_n,ħ)\in\mathbb{R}^{6n+m}$, where m can be either 1 or 3 or 6, form a complete set of variables. In addition, an object O_i translated by a vector v_i and rotated through angles θ_i is designated by $O_i(u_i)$ and a container $\mathbb{C}$ with variable size $ħ$ is denoted as $\mathbb{C}(ħ)$.

3. Mathematical model

On the ground of phi-functions [17,18] and quasi-phi-functions [19,20], a mathematical formulation of the problem can be stated as follows:

$$(u^{¿},ħ^{¿},Z^{¿})=argmin\,H(ħ)\,s.t.(u,ħ,Z)\in\Lambda\subset\mathbb{R}^N \tag{1}$$

$$\Lambda=\{(u,ħ,Z)\in\mathbb{R}^N:\Phi_{ij}(u_i,u_j,\mathbb{Z}_{ij})\geq 0,i<j\in I,\ \Phi_i(u_i,ħ)\geq 0,i\in I,L(ħ)\geq 0\} \tag{2}$$

where

$$H(ħ)=\begin{cases}(w_2-w_1¿)(l_2-l_1)(\eta_2-\eta_1)\,if\,\mathbb{C}=\mathbb{C}_1,\\ (h_2-h_1)r^2\,if\,\mathbb{C}=\mathbb{C}_2,\\ r^3\,if\,\mathbb{C}=\mathbb{C}_3,\end{cases}$$

$$L(ħ)=\begin{cases}w_1\geq 0,l_1\geq 0,\eta_1\geq 0,w_2-w_1\geq 0,l_2-l_1\geq 0,\eta_2-\eta_1\geq 0\,if\,\mathbb{C}=\mathbb{C}_1,\\ h_2-h_1\geq 0,h_1\geq 0,r\geq 0\,if\,\mathbb{C}=\mathbb{C}_2,\\ r\geq 0\,if\,\mathbb{C}=\mathbb{C}_3,\end{cases}$$

$$N\geq 6n+m,\ m=\begin{cases}6\,if\,\mathbb{C}=\mathbb{C}_1,\\ 3\,if\,\mathbb{C}=\mathbb{C}_2,\\ 1\,if\,\mathbb{C}=\mathbb{C}_3.\end{cases}$$

Here, the inequality $\Phi_{ij}(u_i,u_j,\mathbb{Z}_{ij})\geq 0$ ensures non-overlapping O_i and O_j while the inequality $\Phi_i(u_i,ħ)\geq 0$ guarantees a containment of O_i within $\mathbb{C}(ħ)$ i.e. $\Phi_i(u_i,ħ)$ is a *phi*-function for O_i and $B(ħ)=\mathbb{R}^3\setminus int\,\mathbb{C}(ħ)$ where $int\,\mathbb{C}(ħ)$ is the interior of $\mathbb{C}$. A vector $\mathbb{Z}_{ij}$ can consist of at most q components.

Let us examine the fundamental properties of the mathematical model.

Since $O_i=\bigcup_{s=1}^{\epsilon_i}O_{is}$ and $O_j=\bigcup_{p=1}^{\epsilon_j}O_{jp}$, then $O_i\cap O_j=\varnothing$ if $O_{is}\cap O_{jp}=\varnothing$, $s\in K_i$, $p\in K_j$. Consequently $\Phi_{ij}(u_i,u_j,\mathbb{Z}_{ij})=min\{\Phi_{ij}^{sp}(u_i,u_j,\mathbb{Z}_{ij}^{sp}),\ s\in K_i,\ p\in K_j\}$ where $\Phi_{ij}^{sp}(u_i,u_j,\mathbb{Z}_{ij}^{sp})$ is either a Φ-function or a quasi-phi-function for O_{is} and O_{jp}. Thus, $\Phi_{ij}(u_i,u_j\mathbb{Z}_{ij})\geq 0$ if $min\{\Phi_{ij}^{sp}(u_i,u_j,\mathbb{Z}_{ij}^{sp}),s\in K_i,p\in K_j\}\geq 0.$

Each quasi Φ-function $\Phi_{ij}^{sp}(u_i,u_j,\mathbb{Z}_{ij}^{sp})$ in general, is a function of the kind $\Phi_{ij}^{sp}(u_i,u_j,\mathbb{Z}_{ij}^{sp})=max\{\Psi_{ij}^{spa}(u_i,u_j,\mathbb{Z}_{ij}^{sp}),\ a\in A_{ij}^{sp}=B_{ij}^{sp}\cup\mathbb{C}_{ij}^{sp}=\{1,2,\dots,a_{ij}^{sp}+1,a_{ij}^{sp}+2,\dots,\varkappa_{ij}^{sp}\}\}$. Thus, $\Phi_{ij}^{sp}(u_i,u_j,\mathbb{Z}_{ij}^{sp})\geq 0$ if no fewer than one of the inequality systems $\{\Psi_{ij}^{spa}(u_i,u_j,\mathbb{Z}_{ij}^{sp})\geq 0,a\in A_{ij}^{sp}$, holds true. It is evident $\Phi_{ij}(u_i,u_j,\mathbb{Z}_{ij})\geq 0$ if at least one of the inequality systems $\{\Psi_{ij}^{spa}(u_i,u_j,\mathbb{Z}_{ij}^{sp})\geq 0,s\in K_i,p\in K_j$, where $a\in A_{ij}^{sp}$ is satisfied. So, the number of systems is $\varsigma_{ij}=\prod_{s=1}^{\kappa_i}\prod_{p=1}^{\kappa_j}\varkappa_{ij}^{sp}$.For the sake of convenience, we rename the inequality systems as

$$\{\Psi_{ij}^{t}(u_i,u_j,\mathbb{Z}_{ij}^{t})\geq 0,t\in T_{ij}=\{1,2,\dots,\varsigma_{ij}\}.$$

It follows from the previous items that $\Phi_{ij}(u_i,u_j,\mathbb{Z}_{ij})\geq 0,\ i<j\in I$, if at least one of the inequality systems $\left\{\Psi_{ij}^{t}(u_i,u_j,\mathbb{Z}_{ij}^{t})\geq 0, i<j\in I\right.$, where $t\in T_{ij}$, holds true. For the sake of convenience, we rename the inequality systems as

$G_\tau(u,\mathbb{Z})\geq 0, \tau\in Y=\{1,2,\dots,\vartheta\}$

where $\vartheta=\prod_{i=1}^{n}\prod_{j}^{n}\varsigma_{ij}$.

Each function of the family $\Psi_{ij}^{spa}(u_i,u_j,\mathbb{Z}_{ij}^{sp}), a\in\mathbb{C}_{ij}^{sp}$ contains an additional vector $\mathbb{Z}_{ij}^{sp}$ consisting in general of several components. This means that each inequality system contains at most $\prod_{i=1}^{\kappa_i}\prod_{j=1}^{\kappa_i}\kappa_i\kappa_j$ variables.

Each function $\Phi_i(u_i,\hbar)$is presented as

$$\Phi_i(u_i,\hbar)=min\{\Phi_{is}(u_i,\hbar), s\in K_i=\{1,2,\dots,\kappa_i\}\}$$

where $\Phi_{is}(u_i,\hbar)$ is the Φ-function for O_{is} and $C(\hbar)=R^3\backslash int\,\mathbb{C}(\hbar)$.

Based on items 3 and 4 we draw a very important conclusion: the feasible region Λ can be presented as follows:

$$\Lambda=\bigcup_{\tau=1}^{\vartheta}\Lambda_\tau,$$

where Λ_τ is specified by the inequality system

$$F_\tau(u,\hbar,\mathbb{Z}_\tau)=\begin{cases}G_\tau(u,\mathbb{Z}_\tau)\geq 0,\\ \Phi_i(u_i,\hbar)\geq 0, i\in I,\\ L(\hbar)\geq 0,\end{cases}=\begin{cases}f_{\tau 1}(\xi_{\tau 1})\geq 0,\\ f_{\tau 2}(\xi_{\tau 2})\geq 0,\\ \dots\dots\dots\dots\\ f_{\tau\epsilon}(\xi_{\tau\epsilon})\geq 0\end{cases}$$

where $\xi_{\tau t}$ consists of components of vectors u and $\mathbb{Z}_\tau$, $\epsilon>\prod_{i=1}^{\kappa_i}\prod_{j=1}^{\kappa_i}\kappa_i\kappa_j+n\prod_{i=1}^{n}\kappa_i$.

Note that the functions $f_{\tau j}(\xi_{\tau j}),\ j=1,2,\dots,\epsilon$, are smooth with respect to their variables.

Consequently, solving the problem (1) – (2) can be reduced to solving step by step the following subproblems:

$$(u^{i\tau},\hbar^{i\tau})=argmin\,H(\hbar)\,s.t.(u,\hbar)\in\Lambda_\tau\subset\mathbb{R}^N,\tau\in Y.$$

This means we have a theoretical chance to compute a global minimum solution of the problem (1) – (2).

4. Solution algorithm

Since the solution space of the stated problem is defined by many inequalities, we propose solving the problem (1)–(2) in stages to obtain a local minimum point within a reasonable time.

1. Derivation of starting points from the feasible region.

- First of all, we cover objects O_i by spheres S_i of minimum radii $r_i^0, i\in I$.
- Then we pack in pairs of objects $O_i, i\in I$, into clusters to be either cuboids or spheres of minimum volumes. (If the number n of geometric objects is less than 30, then we cover O_i by spheres S_i of minimum radii $r_i, i\in I$, and pack the spheres into the container $\mathbb{C}$ with minimum volume).
- We solve a packing problem of the clusters into a container C with minimum volume.
- Next, we take appropriate objects $O_i, i\in I$, instead of spheres $S_i, i\in I$, (in addition, we give rotation angles of $O_i, i\in I$, randomly) or clusters $Q_t, t\in T$, and form a starting point belonging to the feasible region.

2. Calculation of a local minimum.

- We solve the packing problem of objects $O_i, i\in I$,with fixed angle parameters, obtain a local minimum point.

- On the ground of the point and given angle parameters, a starting point is formed, and a local minimum point of the problem (1) – (2) is calculated.

Let us consider the stages in detail.

5. Constructing feasible starting points

5.1. Covering geometric objects with spheres

In order to cover objects O_i with spheres $S_i=\{X\in\mathbb{R}^3,\ x^2+y^2+z^2-r_i^2\le 0\}$ of minimum radii r_i, with placement parameters $v_i=(x_i,y_i,z_i).i\in I$, we solve the following problems:

$$r_i^0=min\, r_i\, s.t.\,(r_i,v_i)\in D_i\subset\mathbb{R}^4, i\in I,$$
$$D_i=\{(r_i^0,v_i^0)\in\mathbb{R}^4,\Phi_i(r_i,v_i)\ge 0\}.$$

Here, $\Phi_i(r_i,v_i)\ge 0$ provides non-overlapping O_i and a set

$$\mathbb{C}_i=\{X\in\mathbb{R}^3,-(x-x_i)^2-(y-y_i)^2-(z-z_i)^2+r_i^2\ge 0\}.$$

As a result of solving the problem, a point (r_i^0,v_i^0) is calculated. In what follows, we remove the origins of the incoordinate systems of O_i so that they coincide with the centers of spheres S_i, $i\in I$. This means that a translation vector of O_i in $\mathbb{R}^3$ is a vector $v_i=(x_i,y_i,z_i)$ which coincides with the centre coordinates of the sphere $\mathbb{C}_i$.

After that, we solve a packing problem of spheres S_i, $i\in I$, into a sphere $\mathbb{C}_3$ of minimum volume if $n\le 30$. The problem is solved just as presented in [18]. Consequently, a point $(v^{\prime},R^{\prime})$ close to a global minimum point is identified. Randomly given rotation angles $\varphi_i=\varphi_i^0,\psi_i=\psi_i^0$ and $\omega_i=\omega_i^0$ of O_i, $i\in I$, we form a starting point $(u^0,\theta^0)=(v^{\prime},\varphi^0,\psi^0,\omega^0)\in\Lambda$ for the problem (1) – (2) for $\mathbb{C}=\mathbb{C}_3$.

5.2. Pairwise packing of objects into clusters

Let O_i, $i\in I$, consist of k groups each containing l_k identical geometric objects. We pack in pairs O_i, $i\in I$, into cuboids Q_{ij} of the minimum volumes V_{ij}^C, $i<j\in K=\{1,2,\dots k\}$. To this end, we solve the problems

$$V_{ij}^C=F_{ij}(\hbar^{\circ})=min\, F_{ij}(\hbar)\, s.t.\,(u_i,u_j,\hbar)\in\Omega_{ij}\subset\mathbb{R}^{18}, i<j\in I, \tag{3}$$

where

$$F_{ij}(\hbar)=(w_2^{ij}-w_1^{ij})(l_2^{ij}-l_1^{ij})(\eta_2^{ij}-\eta_1^{ij}),$$
$$\Omega_{ij}=\{(u_i,u_j,\hbar)\in\mathbb{R}^{18}:\Phi_{ij}(u_i,u_j)\ge 0,\Phi_i(u_i,\hbar)\ge 0,\Phi_j(u_j,\hbar)\ge 0,L_{ij}(\hbar)\ge 0\},$$
$$L_{ij}(\hbar)=(w_1^{ij}\ge 0,l_1^{ij}\ge 0,\eta_1^{ij}\ge 0,w_2^{ij}-w_1^{ij}\ge 0,l_2^{ij}-l_1^{ij}\ge 0,\eta_2^{ij}-\eta_1^{ij}\ge 0).$$

The inequality $\Phi_{ij}(u_i,u_j)\ge 0$ insures $int\, O_i\cap int\, O_j=\varnothing$ while $\Phi_i(u_i,\hbar)\ge 0$ guarantees a placement of O_i within Q_{ij}.

Consequently, a local minimum point $(u_i^{\prime},u_j^{\prime},\hbar^{\prime})$ close to a global minimum for the problem (3) is computed.

After that, we pack in pairs O_i, $i\in I$, into spheres S_{ij} of the minimum radius $R_{ij}^{\prime}$, $i<j\in K=\{1,2,\dots,k\}$, i.e. we solve the following problems:

$$V^S=\frac{4}{3}\pi\, min\,\{R_{ij}^3,i<j\in I\}\, s.t.\,(u_i,u_j,R_{ij})\in\Omega_{ij}\subset\mathbb{R}^{13},$$

where

$$\Omega_{ij}=\{(u_i,u_j,R_{ij})\in\mathbb{R}^{16}:\Phi_{ij}(u_i,u_j)\ge 0,\Phi_i(u_i,R_{ij})\ge 0,\Phi_j(u_j,R_{ij})\ge 0,R_{ij}\ge 0\}.$$

The inequality $\Phi_{ij}(u_i,u_j)\ge 0$ provides $int\, O_i\cap int\, O_j=\varnothing$ while $\Phi_i(u_i,\hbar)\ge 0$ insures arrangement of O_i within S_{ij}.

Let point (u_i^*, u_j^*, R_{ij}^*) be an approximate point to a global minimum point of the problem.

To derive a starting point belonging to Ω_{ij}, we introduce homothetic coefficients h_i of objects O_i and O_j and assume that the coefficients are variable. Thus, we have the opportunity to enlarge or diminish sizes of objects O_i and O_j changing their homothetic coefficients. Consequently, the phi-function for $O_i(u_i, h_i)$ and $O_j(u_j, h_j)$ depends on h_i and h_j, i.e. the Φ-function takes the form $\Phi_{ij}(u_i, u_j, h_i, h_j)$, and the Φ-function for $O_i(u_i, h_i)$ and $cl(\mathbb{R}^3 \setminus \mathbb{C}_{ij})$ where $\mathbb{C}_{ij}$ is either Q_{ij} or S_{ij}, depends on h_i, i.e. the Φ-function has the kind $\Phi_i(u_i, ħ, h_i)$. Since for any $0<h_i<\infty$, objects $O_i(u_i, h_i)$ are homothetic, then $\Phi_{ij}(u_i, u_j, h_i, h_j)$ and $\Phi_i(u_i, h_i, ħ)$ have the same form for any $0<h_i<\infty$. The homothetic coefficients h_i, $i \in T$, form a vector $h=(h_i, h_j) \in \mathbb{R}^2$. Furthermore, we select such sizes $ħ'$ of container $\mathbb{C}_{ij}(ħ')$ which guarantees placement of objects O_i and O_j into $\mathbb{C}_{ij}(ħ')$ and fix $ħ'$. It permits to formulation the helper problem

$$\sum_{i=1}^{g} h_i^{¿} = max \sum_{i=1}^{g} h_i \, s.t. . (u, h) \in \Delta \subset \mathbb{R}^{14}, \tag{4}$$

where

$$\Delta = \{(u, h) \in \mathbb{R}^{14}, \Phi_{ij}(u_i, u_j, h_i, h_j) \geq 0, \Phi_k(u_k, h_k) \geq 0, \\ h_k \geq 0, h_k - 1 \geq 0, k = i, j\}.$$

A starting point (u_i', u_j', h') for the problem is formed in the following manner. We set $h_k' = 0.01$, $k = i, j$, and randomly assign u' so that $v_k' \in C_{ij}(ħ')$, $k = i, j$. Note that due to $h_k' = 0.01, k \in i, j$, we generally have the point $(u_i', u_j', h') \in \Delta$.

It is evident if $h_k^{¿} = 1$, $k = i, j$, then $(u_i^*, u_j^{*¿}, h^*)$ is a global maximum point of the problem (4), ensuring objects O_i and O_j are packed into $\mathbb{C}_{ij}(ħ')$.

Now taking the point (u_i', u_j', h') as a starting one, we tackle the problem (4) and obtain a global maximum point $(u_i^*, u_j^*, 1)$.

6. Local optimization

6.1. Packing geometric objects without rotations

The stage involves packing objects under fixed rotation angles.

Firstly, we fix the values of the rotation angles $\varphi_i = \varphi_i^0, \psi_i = \psi_i^0$ and $\omega_i = \omega_i^0$, $i \in I$. This means that only translations of objects O_i, $i \in I$ are allowed. In this case, the problem (1) – (2) takes the form

$$H(ħ^{¿}) = min\, H(ħ) \, s.t. . X \in \Theta \subset \mathbb{R}^D \tag{5}$$

where

$$\Theta = \{X = (v, ħ, Z) \in R^D : \Phi_{ij}(v_i, v_j, Z_{ij}) \geq 0, 0 < i < j \in I, \\ \Phi_i(v_i, ħ) \geq 0, i \in I, L(ħ) \geq 0\}, D \geq 3n + m.$$

For computing a local minimum point $(v^{0*}, ħ^{0*}, Z^{0*})$ of the problem, the same solution scheme is applied to solving the problem (1) – (2).

6.2. Searching for a local minimum point of the basic problem

Now we continue to search for a local minimum point $(u^{0*}, ħ^{0*}, Z^{0*})$ of the problem (1) – (2), beginning with a starting point $(u^0, ħ^0, Z^0) = (v^{0*}, \theta^0, ħ^{0*}, Z_\kappa^{0*}) \in \Lambda$ where rotation angles θ^0 and $(v^{0*}, ħ^{0*}, Z_\kappa^{0*})$ are taken from a local minimum point of the problem (5). This stage consists of

several steps, which are reduced to solving a sequence of substantially simpler subproblems regarding the number of inequalities and the dimensions of the solution space.

Computing a local minimum point $(v^*, \hbar^*, \mathbb{Z}^*)$ of the problem (1) – (2) can be reduced to solving a sequence of subproblems

$$H(\hbar^{(\kappa+1)*}) = \min H(\hbar)\, s.t.\, X \in \Lambda_\kappa, \varkappa = 0,1,2,.... \quad (6)$$

For each starting point $(u^{\kappa *}, \hbar^{\kappa *}, Z_\varkappa^*) \in \Lambda$ a subregion Λ_κ containing the point $(u^{\kappa *}, \hbar^{\kappa *}, Z_\varkappa^*)$ is singled out. A starting point is $(u^{0*}, \hbar^{0*}, Z_0^*) = (u^0, \hbar^0, Z_0^0)$. A vector $\mathbb{Z}_\varkappa^{¿}$ is constructed specially.

The computational process proceeds until $H(\hbar^{(\kappa+1)*}) = H(\hbar^{\kappa *})$ is fulfilled. This indicates that the point $(u^{\kappa *}, \hbar^{\kappa *}, Z_\varkappa^*)$ is a local minimum point of the problem (1) – (2).

6.3. Transition between feasible subregions

Since $(u^{\kappa *}, \hbar^{\kappa *}, Z_\varkappa^*)$ being a local minimum point of the problem $H(\hbar^{\kappa *}) = \min H(\hbar)$ s.t. $X \in \Lambda_\kappa$ is not in generally a local minimum point of the problem (1) – (2), we need to transition to another region $\Lambda_{\kappa+1}$ which ensures the value of $H(\hbar)$ does not worsen at the local minimum point ¿n the new region $\Lambda_{\kappa+1}$.

Let $f_{i_{j\kappa}}(\xi_{i_j}) \ge 0$, $j \in N_\kappa$, be active inequalities at the point $(u^{\kappa *}, \hbar^{\kappa *}, Z_\varkappa^*)$. We single out inequality subsystems $\Psi_{ij}^{spA}(u_i, u_j, \mathbb{Z}_{ij}^{spa}) \ge 0$, $i \in E_{1\kappa}, j \in E_{2\kappa}$, $s \in K_{i\kappa}, p \in K_{j\kappa}$, $a = a_{ij}^{sp}$, where t_{ij}^{sp} is from the index set A_{ij}^{sp}, which contain the active inequalities. Note that $\Psi_{ij}^{spa}(u_i^\kappa, u_j^\kappa, \mathbb{Z}_{ij}^{spa}) = 0$, $i \in E_{1\kappa}, j \in E_{2\kappa}, s \in K_{i\kappa}, p \in K_{j\kappa}$.

Next, we single out inequalities $\Phi_{ij}^{sp}(u_i, u_j, \mathbb{Z}_{ij}^{sp}) \ge 0$ from the inequality system (2), which incorporates the inequality subsystems $\Psi_{ij}^{spa}(u_i, u_j, \mathbb{Z}_{ij}^{spa}) \ge 0$, $i \in E_{1\kappa}^0 \subset E_{1\kappa}, j \in E_{2\kappa}^0 \subset E_{2\kappa}, s \in K_{i\kappa}^0 \subset K_{i\kappa}, p \in K_{j\kappa}^0 \subset K_{j\kappa}$, $t = t_{ij}^{sp}$. Then, we compute the components $\mathbb{Z}_{ij}^{spa}$, $i \in E_{1\kappa}^0, j \in E_{2\kappa}^0, s \in K_{i\kappa}^0, p \in K_{j\kappa}^0$, $a \in C_{ij}^{sp}$, as the solution to the problems and select components Z_{ij}^{spt}, $t \in C_{ij\varkappa}^{sp} \subset C_{ij}^{sp}$ for which $\Psi_{ij}^{spa}(u_i^{\kappa *}, u_j^{\kappa *}, Z_{ij}^{sa*})_{ij}^{sp*} > 0$.

After that, we compute $\Phi_{ij}^{sp}(u_i^\kappa, u_j^\kappa, \mathbb{Z}_{ij}^{spa}) = k_{ij}^{spa}$, $i \in E_{1\kappa}, j \in E_{2\kappa}, s \in K_{i\kappa}$, $p \in K_{j\kappa}, a \in B_{ij}^{sp} \cup C_{ij\varkappa}^{sp}$. Since each of $\Phi_{ij}^{sp}(u_i, u_j, \mathbb{Z}_{ij}^{spa})$, $i \in E_{1\kappa}, j \in E_{2\kappa}, s \in K_{i\kappa}, p \in K_{j\kappa}$, includes operation max then some of k_{ij}^{spt}, $i \in E_{1\kappa}, j \in E_{2\kappa}, s \in K_{i\kappa}, p \in K_{j\kappa}$, $t \in B_{ij\varkappa}^{sp} \cup C_{ij\varkappa}^{sp}$ ($B_{ij\varkappa}^{sp} \subset B_{ij}^{sp}$) can be found strictly positive. Let $\Phi_{ij}^{sp}(u_i^\kappa, u_j^\kappa, Z_{ij}^{spq}) = \Psi_{ij}^{spq}(u_i^\kappa, u_j^\kappa, \mathbb{Z}_{ij}^{spq}) = k_{ij}^{spq} > 0$, $i \in E_{1\kappa}^0 \subset E_{1\kappa}^1, j \in E_{2\kappa}^0 \subset E_{2\kappa}^0$, $s \in K_{i\kappa}^0 \subset K_{i\kappa}$, $p \in K_{j\kappa}^0 \subset K_{j\kappa}$, $q \in B_{ij\varkappa}^{sp} \cup C_{ij\varkappa}^{sp}$ where $B_{ij\varkappa}^{sp} \subset B_{ij}^{sp}$. Since $a \ne q$ for all $i \in E_{1\kappa}^0, j \in E_{2\kappa}^0$, $s \in K_{i\kappa}^0, p \in K_{j\kappa}^0$, $a \in B_{ij\varkappa}^{sp} \cup C_{ij\varkappa}^{sp}$, we can derive a new inequality system $F_{\kappa+1}(u, \hbar, \mathbb{Z}_{\varkappa+1}) \ge 0$ specifying a new feasible subregion $\Lambda_{\kappa+1}$ by substituting the inequality subsystems $\Psi_{ij}^{spa}(u_i, u_j, \mathbb{Z}_{ij}^{spa}) \ge 0$, $i \in E_{1\kappa}^0, j \in E_{2\kappa}^0, s \in K_{i\kappa}^0, p \in K_{j\kappa}^0$, $t = t_{ij}^{sp}$, in the system $F_\kappa(u, \hbar, \mathbb{Z}_\varkappa) \ge 0$ for the inequality subsystems $\Psi_{ij}^{qrq}(u_i, u_j, Z_{ij}^{spq}) \ge 0$, $i \in E_{1\kappa}^0, j \in E_{2\kappa}^0, q \in K_{i\kappa}^0, r \in K_{j\kappa}^0$, $q = q_{ij}^{sp}$. Furthermore, a new vector $\mathbb{Z}_\varkappa^{¿}$ which includes new components of the set $\mathbb{Z}_{ij}^{spq}$, $q \in B_{ij\varkappa}^{sp} \cup C_{ij\varkappa}^{sp}$, is formed. It is evident that $(u^{\kappa *}, \hbar^{\kappa *}, Z_\varkappa^*) \in \Theta_{\kappa+1}$. Thus, if at least one $k_{ij}^{spq} > 0$, then we obtain a new inequality system $F_{\kappa+1}(u, \hbar, \mathbb{Z}_{\kappa+1}) \ge 0$ specifying a set $\Lambda_{\kappa+1} \ne \Lambda_\kappa$ and a new starting point ¿ where a new vector $Z_\kappa^{¿}$ includes components $\mathbb{Z}_{ij}^{spt}$, $t \in B_{ij\varkappa}^{sp} \cup C_{ij\varkappa}^{sp}$. It follows from the construction that a starting point $(u^{\kappa *}, \hbar^{\kappa *}, Z_\kappa^*)$ provides $H(\hbar^{(\kappa+1)*}) \le H(\hbar^{\varkappa *})$.

6.4. Computing a local minimum point on a feasible subregion

Since inequality system $F_\kappa(u, \hbar, \mathbb{Z}) \ge 0$ consists in general of a huge number of inequalities, the computation of local minimum point $(u^{¿}, \hbar^{¿}, \mathbb{Z}^{¿})$ of the problem

$$F(\hbar^{(\kappa+1)*}) = minF(\hbar)\, s.t.\,(u,\hbar,\mathbb{Z}) \in \Lambda_\kappa, \tag{7}$$

is also derived in stages.

Let a point $(u^{\kappa*}, \hbar^{\kappa*}, Z_\kappa^*) \in \Lambda_\kappa$ and some $\delta>0$. Making use of spheres S_i with radii r_i^0, $i \in I$, we select $\Psi_{ij}^{spt}(u_i, u_j, \mathbb{Z}_{ij}^{spt}) \geq 0$, $i \in A_{1\kappa}^t$, $j \in A_{2\kappa}^t$, $s \in K_i$, $p \in K_j$, $t = t_{ij}^{sp}$, from an inequality system $F_\kappa(v, \hbar, \mathbb{Z}_\varkappa) \geq 0$ for which the inequalities $\left\| v_i^{\kappa*} - v_{i_j}^{\kappa*} \right\| - (r_i^0 + r_j^0) \leq \delta, i \in A_{1\kappa}^t, j \in A_{2\kappa}^t$, hold true.

Let $\mathbb{C} = \mathbb{C}_1$. In this case, we single out the inequalities $\Phi_{ik}^f(u_i, \hbar) \geq 0$, $i \in I_{f\kappa}$, $s \in K_i$, $f \in Y = \{1,2,..,6\}$, where $\Phi_{ik}^l(u_i, \hbar)$ is a Φ-function for an object O_{is} and f-th half space, for which the inequalities

$$w_1 - x_i^{\kappa*} - r_i^0 \leq \frac{\delta}{2}, i \in I_{1\kappa}, x_i^{\kappa*} + r_i^0 - w_2 \leq \frac{\delta}{2}, i \in I_{2\kappa},$$
$$l_1 - y_i^{\kappa*} - r_i^0 \leq \frac{\delta}{2}, i \in I_{3\kappa}, y_i^{\kappa*} + r_i^0 - l_2 \leq \frac{\delta}{2}, i \in I_{4\kappa},$$
$$\eta_1 - z_i^{\kappa*} - r_i^0 \leq \frac{\delta}{2}, i \in I_{5\kappa}, z_i^{\kappa*} + r_i^0 - \eta_2 \leq \frac{\delta}{2}, i \in I_{6\kappa}$$

are fulfilled.

Next, we cover convex objects O_{ik} with spheres $\mathbb{C}_{ik}$ of minimum radii ρ_{ik} and centers $v_{ik} = (x_{ik}, y_{ik}, z_{ik}), i \in I$, $k \in K_i$. We suppose that the origins of the local coordinate systems of O_{ik} coincide with the centers $\mathbb{C}_{ik}, i \in I$, $k \in K_i$. Then, the coordinates of centers of circles $\mathbb{C}_{ik}$ with respect to the global coordinate systems of O_i are $v_{ik}(u_i) = (x_{ik}(u_i), y_{ik}(u_i), z_{ik}(u_i)) = R_i^T(v_{ik} + v_i)$, $i \in I, k \in K_i$.

Now let us choose inequalities $\Psi_{ij}^{spt}(u_i, u_j, \mathbb{Z}_{ij}^{spt}) \geq 0$, $i \in A_{1\kappa}^{0t} \subset A_{1\kappa}^t$, $j \in A_{2\kappa}^{0t} \subset A_{2\kappa}^t$, $s \in K_i^t \subset K_i$, $p \in K_j^t \subset K_j$, and $\Phi_{ik}^f(u_i, \hbar) \geq 0$, $i \in I_{f\kappa}$, $s \in K_{\varkappa i}^f \subset K_i$, $f \in Y$, for which the inequalities

$$\|v_{is}(u_i^{\kappa*}) - v_{jp}(u_i^{\kappa*})\| - (\rho_{is} + \rho_{jp}) \leq \delta, i \in A_{1\kappa}^{0t}, j \in A_{2\kappa}^{0t}, s \in K_i^t, p \in K_j^t,$$
$$w_1 - x_{ik}\left(u_i^{\kappa*}\right) - r_i^0 \leq \frac{\delta}{2},, i \in I_{1\kappa}, k \in K_{\varkappa i}^1, x_i\left(u_i^{\kappa*}\right) + r_i^0 - w_2 \leq \frac{\delta}{2}, i \in I_{2\kappa}, k \in K_{\varkappa i}^2,$$
$$l_1 - y_i\left(u_i^{\kappa*}\right) - r_i^0 \leq \frac{\delta}{2},, i \in I_{3\kappa}, k \in K_{\varkappa i}^3, y_i\left(u_i^{\kappa*}\right) + r_i^0 - l_2 \leq \frac{\delta}{2}, i \in I_{4\kappa}, k \in K_{\varkappa i}^4,$$
$$\eta_1 - x_i\left(u_i^{\kappa*}\right) - r_i^0 \leq \frac{\delta}{2}, i \in I_{5\kappa}, k \in K_{\varkappa i}^5, x_i\left(u_i^{\kappa*}\right) + r_i^0 - \eta_2 \leq \frac{\delta}{2}, i \in I_{6\kappa}, k \in K_{\varkappa i}^6,$$

are satisfied respectively.

Taking inequalities $\Psi_{ij}^{spt}(u_i, u_j, Z_{ij}) \geq 0$, $i \in A_{1\kappa}^{0t}, j \in A_{2\kappa}^{0t}, s \in K_i^t$, $p \in K_j^t$, $\Phi_{ik}^f(u_i, \hbar) \geq 0$, $i \in I_{f\kappa}$, $s \in K_{\varkappa i}^f \subset K_i$, $f \in Y$, and $L(\hbar) \geq 0$, we form the inequality subsystem

$$F_{\kappa t}(u, \hbar, \mathbb{Z}_\varkappa) = \begin{cases} \Psi_{ij}^{spt}(v_i, v_j, Z_{ij}) \geq 0, i \in A_{1\kappa}^{0t}, j \in A_{2\kappa}^{0t}, s \in K_i^t, p \in K_j^t, \\ \Phi_{ik}^f(u_i, \hbar) \geq 0, i \in I_{f\kappa}, s \in K_{\varkappa i}^f \subset K_i, f \in Y, \\ L(\hbar) \geq 0, \\ \|v_{is}(u_i^{\kappa*}) - v_{st}(u_i)\| \leq \frac{\delta}{2}, i \in A_{1\kappa}^{0t}, s \in K_i^f \\ \|v_{is}(u_i^{\kappa t})\kappa* - v_{jp}(u_i)\| \leq \frac{\delta}{2}, j \in A_{2\kappa}^{0t}, p \in K_i^f, \end{cases} = \begin{cases} f_{i_1\kappa t}(\xi_{i_1}) \geq 0 \\ f_{i_2\kappa t}(\xi_{i_2}) \geq 0 \\ ..... \\ f_{i_q\kappa t}(\xi_{i_q}) \geq 0 \end{cases}.$$

which describes a subregion $\Lambda_{\kappa t}$ such that $X^\kappa \in (u^{\kappa*}, \hbar^{\kappa*}, Z_\kappa^*) \in \Lambda_{\kappa t} \subset \Lambda_\kappa$.

Consequently, searching for a local minimum point of the problem (1) – (2)can be reduced to solving a sequence of subproblems

$$F\left(\hbar^{\kappa(t+1)}\right)=minF\left(\hbar\right)s.t.\left(u,\hbar\right)\in\Lambda_{\kappa t},t=0,1,2,\ldots, \tag{8}$$

where a local minimum point $\left(u^{\kappa t},\hbar^{\kappa t},Z^{\kappa t}\right)$ of the $\left(t-1\right)$-th problem is taken as a starting point for the t-th problem, and the point $\left(u^{\kappa *},\hbar^{\kappa *},\mathbb{Z}_{\kappa}^{*}\right)$ is taken as a starting point for $t=0.$

The problems are solved until $F\left(\hbar^{\kappa(t+1)}\right)=F\left(\hbar^{\kappa t}\right)$ is met, and the point $\left(u^{\kappa *},\hbar^{\kappa *},\mathbb{Z}_{\kappa}^{*}\right)$ is taken as a local minimum point of the problem (8).

We can diminish the problem dimension for each t. Considering a starting point $\left(u^{\kappa l},\hbar^{\kappa l},\mathbb{Z}^{\kappa l}\right)$ for the problem $F\left(\hbar^{\kappa(t+1)}\right)=minF\left(\hbar\right)$ s.t. $\left(v,\hbar\right)\in\Lambda_{\kappa t}$, we fix $\mathbb{Z}^{\kappa t}$ (i.e., appropriate components of $Z^{\varkappa t}$ do not vary). This means that $\Gamma_{\kappa t}\left(u,\hbar\right)=F_{\kappa t}\left(u,\hbar,\mathbb{Z}^{\kappa t}\right)$ and specifies the feasible subregion $\Lambda_{\kappa t}^{z}$ whose dimension is less than that of $\Lambda_{\kappa t}$. It evident that $\left(u^{\kappa t},\hbar^{\kappa t}\right)\in\Delta_{\kappa t}^{z}$ and all points of $\Delta_{\kappa l}^{z}$ ensure non-overlapping objects O_i, $i\in I$. Thus, we solve a sequence of problems $H\left(\hbar^{\kappa(t+1)}\right)=minH\left(\hbar\right)s.t.\left(u,\hbar\right)\in\Delta_{\kappa t}^{z},t=1,2,\ldots,$ until $H\left(\hbar^{\kappa(t+1)}\right)=H\left(\hbar^{\kappa t}\right)$ is met. Obviously, the point $\left(u^{\kappa(t+1)},\hbar^{\kappa(t+1)},\mathbb{Z}^{\kappa t}\right)$ is not generally a local minimum point of the problem (8).

Taking the point $\left(u^{\kappa(t+1)},\hbar^{\kappa(t+1)},\mathbb{Z}^{\kappa t}\right)$ as a starting one, we continue to solve the problems (8) until a local minimum point $\left(u^{¿},\hbar^{¿},\mathbb{Z}^{¿}\right)$ of the problem (1) is obtained.

7. Computational modelling and numerical results

The efficacy of the proposed methodology is substantiated through the presentation of several case studies. The experiments were conducted on an Intel Core i5-750 computer, utilizing the IPOPT code for local optimization developed by [20].

IPOPT (Interior Point Optimiser) is a distinguished open-source solution for nonlinear optimization problems (NLPS), particularly when dealing with substantial datasets. The subsequent points highlight IPOPT's strengths, substantiated by insights gleaned from the given points:

1. Effective Performance with Large-Scale Challenges.

Utilization of Sparse Matrices: IPOPT employs sparse linear algebra techniques (MUMPS) to address extensive NLPS efficiently. This approach leads to a reduction in memory requirements and an acceleration in processing times.

Parallel linear solvers: The capacity to integrate with parallel solvers, such as HSL MA97 and MUMPS via MPI, provides the scalability necessary for high-dimensional problems.

Finally, IPOPT, an extension, reuses KKT matrix factorizations generated by IPOPT. This approach enables sensitivity calculations with minimal added computational expense, offering gains for parametric analysis and model predictive control.

2. A Reliable and Robust Algorithmic Approach

Interior-point methods: IPOPT utilizes a barrier method to address inequality constraints by incorporating logarithmic penalties. This ensures stability even when confronting degenerate scenarios.

Hybrid optimization methods: IPOPT employs an intelligent blend of gradient-based optimizers, such as the quasi-Newton L-BFGS, with exact Hessian information to achieve accelerated convergence.

Finally, the paper discusses penalty methods. Implementing penalty methods enhances the robustness of the approach when confronted with degenerate nonlinear programming (NLP) problems. This technique meticulously balances feasibility and optimality, yielding superior outcomes compared to standard barrier methodologies in complex scenarios.

3. The flexibility in problem formulation constitutes a significant advantage of IPOPT.

Mathematical Programming with Equilibrium Constraints (MPCC): A notable feature of IPOPT is its ability to circumvent the need for mixed-integer formulations when dealing with non-smooth problems, such as those involving absolute values. This property of IPOPT serves to streamline the implementation process.

Constraint satisfaction: IPOPT can address nonlinear systems by rephrasing them as nonlinear programs (NLPS) that utilize a trivial objective function (e.g., maximizing 0 subject to $f(x) = 0$).

4. Integration with Contemporary Tools.

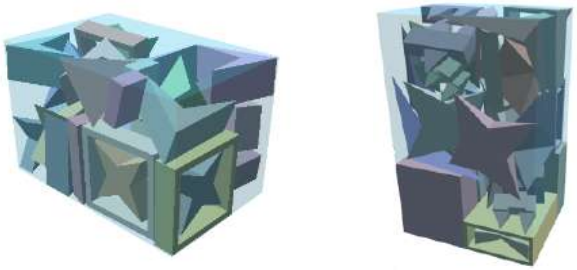
Open-source ecosystem: IPOPT offers seamless interoperability with platforms like Julia, Python, and MATLAB, which enables antidifferentiation capabilities alongside facilitating higher-level modelling approaches.

IPOPT's forte lies in the domain of solving large, sparse NLPs. This is primarily attributable to its advanced interior-point framework, efficient sparse linear algebra integration, and adaptability in addressing many problem types. Furthermore, its open-source foundation and ease of use with modern tools make IPOPT indispensable for chemical engineering, economics, and applications in real-time control systems. Optimized outcomes are achieved by pairing it with high-performance linear solvers, such as HSL MA57, and extensions like IPOPT to facilitate effective sensitivity analysis.

The algorithm was tested on various benchmark instances from [14], with the results summarized below.

For packing 36 objects (Fig. 1a): the HAPE3D approach yielded a volume of 12.4 and a runtime of 963 seconds, while our method attained a volume of 10.7 and a runtime of 750 seconds.

For the case of packing 40 objects (Fig. 1b): the HAPE3D approach achieved a volume of 61.9 and a runtime of 999 seconds, while our method achieved a volume of 56.0 and a runtime of 533 seconds. The results of this study are illustrated in Figure 1.



a b

Figure 1: Comparison of the results obtained with the results presented in [14]: a) 36 non-convex polyhedra; b) 40 non-convex polyhedra.

As demonstrated in Figure 2, the intelligent system developed for this study successfully packed 300 non-convex polyhedra. This result demonstrates the system's capacity to address high-dimensional problems while effectively maintaining adequate time performance.

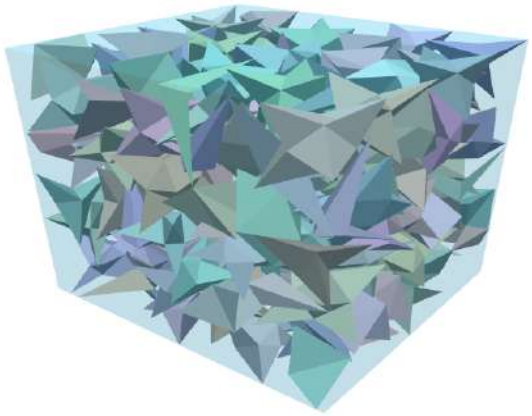


Figure 2: Result of packing of 300 objects

The effectiveness of the proposed approach is confirmed by comparing the results of packing non-convex polyhedra with the results presented by the paper's authors [14]. The results of this comparison are shown in Figure 3.

The results demonstrate that the proposed Intelligent Geometric Modeling Framework significantly reduces computation time and enhances the performance metrics across the test cases.

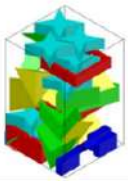
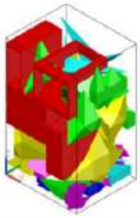
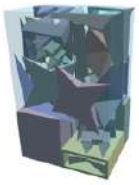
	HAPE3D	*Proposed approach*
The result of packing 36 objects		
Volume	12 480	10 720
Runtime (seconds)	9 637	4 789
Result illustration		
The result of packing 40 objects		
Volume	61 950	56 012
Runtime (seconds)	99 952	24 543
Result illustration		

Figure 3: Comparison of results

8. Conclusions

This article outlines a process for developing an intelligent system focused on geometric design. The proposed systems will leverage cutting-edge methods and tools to automate and improve how geometric shapes are arranged within a three-dimensional environment. The core benefit of these technologies will be their ability to find the best possible solutions when applied to practical challenges in additive manufacturing. Artificial intelligence and other novel techniques will be central to achieving optimal results with these systems.

This research introduces a novel method for precisely modelling the three-dimensional irregular packing problem. Employing the phi-function method, we can leverage contemporary nonlinear optimization techniques to address this challenge, including creating initial configurations and determining local minima.

The clustering technique facilitates starting point generation by solving the packing problem involving half the quantity of convex objects characterized by simpler shapes. This strategic simplification notably diminishes the computational requirements of establishing the initial configurations.

The procedure's computational performance is improved by employing a two-step strategy to locate the local optimum. Initially, a linear problem is addressed. A nonlinear problem then succeeds this in the subsequent stage. The displayed results clearly demonstrate the efficacy of this method in finding solutions for the particular irregular packing problem being studied.

This approach significantly improves the accuracy and efficiency of solving 3D packing issues, which has vital implications for the progress of both natural and information systems. This combination exemplifies a strong synergy between mathematical modelling and advanced computational tools. The approach enhances the precision and efficiency of 3D packing solutions, essential for advancing natural and information systems. This integration demonstrates the powerful collaboration between mathematical models and computational techniques.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Development of physics-informed neural networks for solving partial differential equations

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Abstract

This study evaluates the effectiveness of physics-informed neural networks (PINNs) for solving both stationary and non-stationary partial differential equations (PDEs), including those with Robin boundary conditions, in rectangular and non-rectangular domains. Although only a small subset of the PINN literature examines mixed boundaries or tackles non-rectangular geometries, and even fewer studies benchmark accuracy against the finite-element method (FEM), the present work provides precisely that comparison. We test feedforward PINNs with $\tanh$ activation, whose depth and width were empirically selected for each benchmark to balance accuracy and training cost; training uses Adam optimization with Glorot initialization. These networks are evaluated on three problems: a 2-D Laplace equation on a square (Dirichlet–Neumann–Robin), the same equation on a doubly connected domain with Dirichlet boundary conditions, and a 1-D non-stationary heat equation with Robin boundaries. A weighted mean-squared residual, evaluated via automatic differentiation in TensorFlow, balances equation, boundary, and initial-time terms, thereby handling non-stationary problems without a separate time-stepping scheme. Within the tested class, linear, second-order parabolic and elliptic PDEs in 1-D and 2-D, the network attains $\lesssim 3\ \%$ l_∞error relative to analytical or FEM solutions after 4–6 min of training on an RTX 3080 Ti Laptop GPU, matching FEM accuracy while eliminating meshing and easing equation and boundary changes. The time to compute a standard PINN solution is longer than for a FEM solution for problems considered in the research, and a broad literature review reveals theoretical convergence limits that constrain standard PINNs to modest-scale, well-conditioned diffusion problems.

Keywords

physics-informed learning, PINNs, PDE, automatic differentiation, FEM, boundary conditions

1. Introduction

In the contemporary scientific community, significant attention is dedicated to developing numerical methods for solving differential equations, which have applications across various scientific and engineering fields. A leading technology in this domain is physics-informed neural networks (PINNs) [1, 2, 3], which integrate physical laws directly into the neural network training process [4], ensuring high accuracy and efficiency in solving complex problems. This relies on the universal approximation theorem: any continuous function on a compact set can be approximated arbitrarily well by a sufficiently large multilayer feedforward network with a non-polynomial activation [5].

PINNs have undergone significant advancements, enabling them to solve a broader spectrum of partial differential equations (PDEs), including one-dimensional, nonlinear, and two-dimensional stationary problems [6, 7, 8]. The framework presented in [9] facilitates both forward and inverse problem-solving involving nonlinear PDEs. Recent modifications of PINNs include VPINNs [10], which reformulate the loss function using a variational (weak) formulation to improve robustness, KANN-based models [11] that leverage Kolmogorov–Arnold Networks for enhanced parameter efficiency and faster convergence, and others. While they demonstrate impressive examples, several gaps persist: (i) mixed Robin conditions are rarely tested. To our knowledge, only five studies [12, 13, 14, 15, 16] explicitly address Robin boundary conditions in PINNs, even though the overall PINN literature numbers in the hundreds. Moreover, those works focus on specialized PINN variants rather than the standard PINN formulation employed here; (ii) comparison usually is done with an analytical solution, and FEM is usually absent. Only one of the articles mentioned compares PINN with FEM. To

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our knowledge, the literature still lacks a systematic PINN vs FEM comparison for equations of diffusion type, such as the 2-D Laplace equation and the 1-D heat equation, when mixed Dirichlet–Neumann–Robin conditions are imposed on rectangular domains or when purely Dirichlet boundary conditions are prescribed on non-rectangular geometries. Our work closes these gaps by providing a comparison of [Примітки]diffusion and heat-conduction problems with analytically known or FEM solutions. Also, some papers like [1, 2] use training datasets generated from another solver, while in our approach we only have physics loss.

This research is driven by the need for methods capable of solving physical problems with high accuracy and low computational costs. Traditional numerical methods, such as the finite element method (FEM) [17, 18], often require substantial computational resources and time, especially for multidimensional systems, nonlinear problems, and heterogeneous media.

The goal of this study is to determine the accuracy and computational cost trade-offs under which a mesh-free PINN can replace FEM for linear, second-order parabolic and elliptic PDEs. We demonstrate this on stationary 2-D problems, rectangular domains with mixed boundary conditions and non-rectangular domains with Dirichlet boundary conditions, and on a 1-D non-stationary heat-conduction problem, testing PINN predictions against analytical and FEM solutions.

2. Methodology

A physics-informed neural network is a feedforward neural network that incorporates the laws of physics, which are defined by differential equations, into the learning process. Figure 1 shows a PINN architecture with an input layer, hidden layers, an output layer and components of a loss function.

In our case, the algorithm of this approach can be presented as follows:

- Set datasets for training: for the equation, for the boundary and initial conditions;
- Define the calculation of the necessary derivatives for the equations that are used in the loss function;
- Define the loss function for the equation and boundary conditions;
- Train the PINN to find an approximate solution by minimising the loss function.

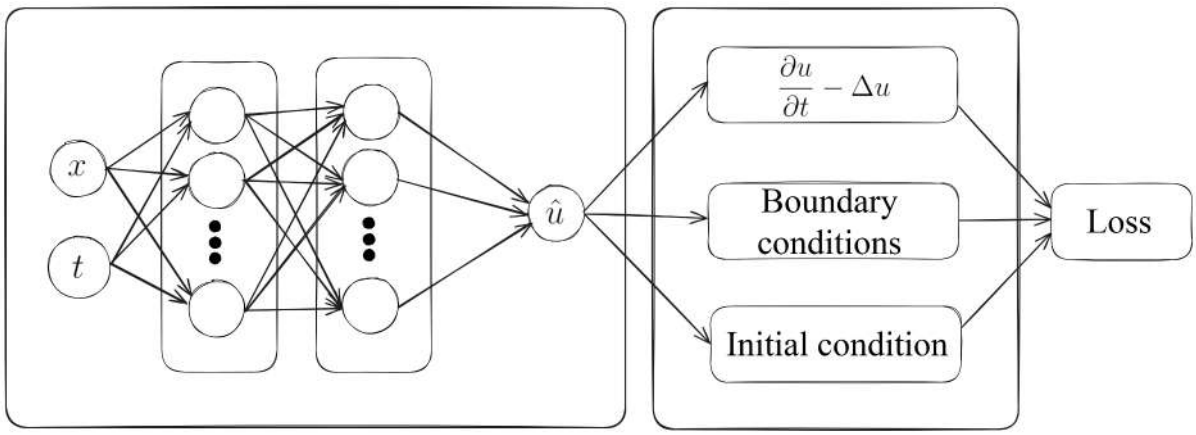

Figure 1: Architecture of a physics-informed neural network for solving the non-stationary heat equation.

It is assumed that all the necessary input data are initially set, after which the neural network is trained, and the values at specific points are predicted. If any of the input parameters are modified, the neural network must be retrained.

The loss function is calculated as the sum of the mean squared errors (MSE) of the equation values, initial and/or boundary conditions.

The MSE is calculated according to formula (1).

$$MSE(e)=\frac{1}{n}\sum_{i=1}^{n} e_i^2, \tag{1}$$

where e is a vector of length n (n is the number of training points) obtained after substituting the obtained approximation from the neural network into the equations or initial/boundary conditions.

The loss function is:

$$L = \lambda_e MSE_e + \lambda_b MSE_b + \lambda_i MSE_i, \quad (2)$$

where MSE_e is the error of satisfaction of the equation, MSE_b is the error of satisfaction of the boundary conditions, MSE_i is the error of satisfaction of the initial condition, λ_e, λ_b and λ_i are weighting factors to balance the influence of different components of the loss function. The magnitudes of residuals of PDE, boundary conditions and initial condition can differ by orders of magnitude, one term may dominate the total loss, preventing the network from accurately enforcing the other conditions; this imbalance motivates careful choice of the weights.

The physics-informed neural networks were developed using Python and TensorFlow (TF) version 2. TensorFlow's automatic differentiation mechanism [19] was used to calculate the values of the loss function and determine all the necessary derivatives, both from the known and the desired function. The Adam (adaptive moment estimation) algorithm [20], a stochastic gradient descent method based on estimates of the first and second moments of gradients, was used to optimize the model's parameters. To initialize the weights, we used the Glorot Normal initialization [21], which initializes the offset value to zero, and the weights for each layer are determined from the normal distribution formula.

For computing the loss and the necessary derivatives in TF, automatic differentiation was used. During the forward pass of the neural network, TF creates a computational graph that stores the operations performed on the tensors and their sequence. In the automatic differentiation step, the chain rule is applied to compute the derivative of the loss function with respect to the weight coefficients and biases based on the computational graph obtained during the forward pass.

The neural networks were trained on an Nvidia GeForce RTX 3080 Ti Laptop graphics card.

The finite element method is implemented using the FEniCS library using piecewise linear basis functions for the approximation.

The Crank-Nicolson method, defined by (3), was used for time discretisation. This method is certainly numerically stable for diffusion equations and beyond. It has a second-order accuracy with respect to Δt.

$$u_{n+1} = u_n + \frac{\Delta t}{2}\left(F_n + F_{n+1}\right), \quad (3)$$

where Δt is the value of the time discretisation step, $u^n - ¿$ is the approximate solution at time $t_n = \frac{n}{N}$, $n \in \{0, 1, 2, \ldots, N\}$ is the time step number, N is the number of time steps, u^0 is the initial condition, F_n is the right-hand side of the non-stationary equation at time t_n.

3. Strengths and Limitations

Advantages of PINNs:

- Flexible problem setup. Changing the governing equations or boundary conditions is straightforward, which makes adapting to new problems easy;
- Geometry-agnostic modeling. PINNs can handle arbitrarily complex domains without requiring a mesh, simplifying the treatment of intricate geometries. Training points density must still reflect local solution scales; poor sampling can harm accuracy;
- Built-in physics knowledge. By embedding the differential equations directly into the network's loss, PINNs leverage a priori knowledge of the problem structure, improving both accuracy and efficiency;
- Multidimensional and time-dependent capability. A single PINN formulation can solve stationary and non-stationary, low- or high-dimensional problems without resorting to separate time-discretization schemes;
- Advanced optimization. They can exploit state-of-the-art training algorithms and regularization techniques to accelerate convergence;
- Interoperability. PINNs integrate seamlessly with other machine-learning algorithms and data-driven methods.

Disadvantages of PINNs:

- Risk of local minima. Like all gradient-descent–based approaches, PINNs can become trapped in local minima, yielding suboptimal solutions;
- Hyperparameter sensitivity. Selecting the optimal network architecture, learning rate, weighting of loss terms, etc., often demands extensive tuning and computational effort;
- No guaranteed convergence. There is no general convergence guarantee for PINN training—particularly on highly nonlinear problems and with multiple local minima, so gradient-based optimization may never find the true (global) solution.
- High computational cost. Training PINNs on large-scale or high-dimensional tasks can require substantial CPU/GPU resources, which may limit their practical use in some settings.

Recent theory proves convergence of PINNs only in narrow settings—e.g., linear second-order elliptic and parabolic PDEs with smooth coefficients (Hölder-continuous) and infinite points samples [22]. For the general nonlinear, stiff, or multimodal (loss landscapes containing many distinct local minima or several alternative solutions) case, no global convergence proof exists; instead, empirical studies reveal gradient-flow pathologies (vanishing, exploding, or mutually orthogonal gradients) that stall training in local minima [23], failure modes in which the network fails to capture even basic physical scenarios [24], and a sharp drop in success probability as PDE order or dimensionality rises [25, 26]. Attempts to fix these issues—loss-term re-weighting [27], curriculum sampling [28] or symmetry [29] — improve robustness but still lack rigorous guarantees. Comprehensive convergence theory therefore remains an open research problem, and practitioners must validate results against reference solvers or a posterior error estimators [30, 31].

4. Results and discussions

4.1. Problem 1

Let us consider the boundary value problem for stationary diffusion:

$$\Delta u = 0, x \in \Omega = (0;1) \times (0;1), \tag{4}$$

$$u = 0 \text{ on } \Gamma_1, \tag{5}$$

$$\frac{\partial u}{\partial n} = 0 \text{ on } \Gamma_2, \tag{6}$$

$$u = 1 \text{ on } \Gamma_3, \tag{7}$$

$$\frac{\partial u}{\partial n} = u \text{ on } \Gamma_4. \tag{8}$$

Table 1
Selected hyperparameters of the neural network for the problem (4)-(8)

Learning speed	Nodes on one axis	Hidden layers	Number of neurons in one layer	Stopping criterion (loss)	Activation function
1e-2	11	3	10	1e-3	tanh

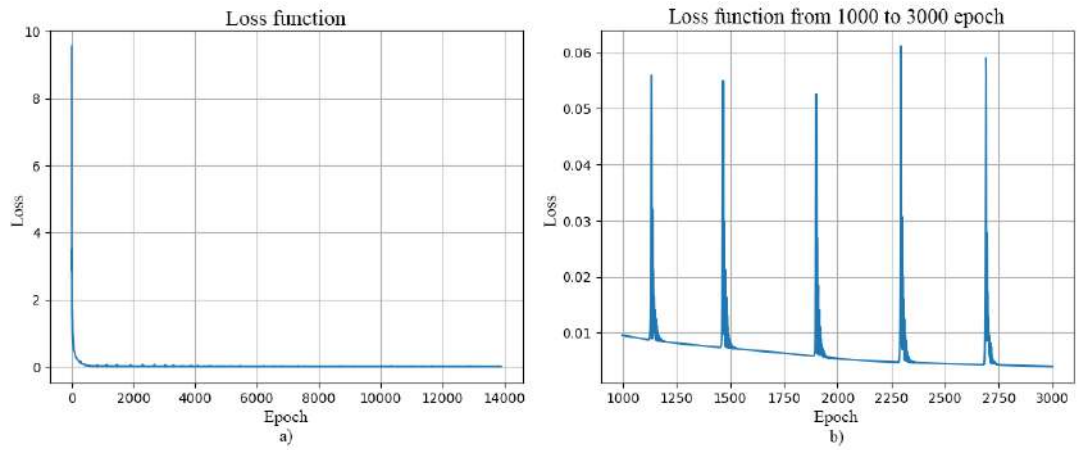

Figure 2: a) The loss function up to the final epoch. b) The loss function from the 1000th to 3000th epoch.

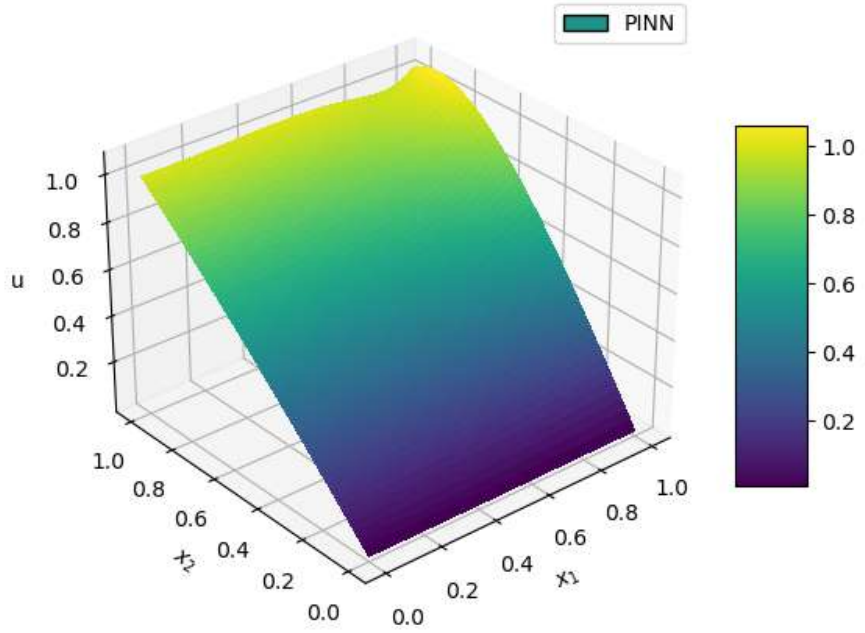

Figure 3: The approximate solution of (4)-(8) obtained by PINN after 13900 epochs.

Figure 2 illustrates that after 1000 epochs the NN achieved loss as low as 0.01, compared to initial value around 9. Also, in Figure 2 b) can be seen how the network tries to get out of local minimum to get a better solution, closer to the global minimum. Figure 3 illustrates solutions obtained by PINN after 13900 epochs of training. This neural network has 261 parameters to train. Training of the PINN took 3 min 49 sec to achieve the loss given in Table 1. The average training time is 4 minutes and 33 seconds among the 5 training sessions. The deviation of the average time from the minimum time in the sample data is 53s, and from the maximum training time is 89s.

To balance the influence of different components of the loss function, the following coefficients were chosen in (2): for Robin's condition on the right boundary Γ_4, $\lambda=2$, all other λ coefficients are equal to one.

For the FEM, linear rectangular finite elements on a 10x10 grid were used.

Figure 4 and Figure 5 show that the approximate solution corresponds to the error in l_∞ norm of 2.92 % calculated in Table 2. In Figure 5, we can clearly see that NN, which is a non-linear function, tries to approximate a line. Therefore, we will always observe some deviations, even as the number of epochs or the number of training points increases.

The relatively low relative error in the l_∞ norm (2.92 %) indicates that the PINN approximates the stationary diffusion problem with high accuracy, comparing favorably with the FEM results. The careful selection of loss coefficients, particularly using $\lambda=2$ for the Robin boundary condition, appears to be instrumental in balancing the contribution of various loss components. This balance is essential to achieve a stable convergence and accurate solution. Overall, these findings suggest that

PINN is a viable alternative for solving such boundary value problems, especially when rapid adjustments to the problem setup are required.

Table 2
Error between the approximate solutions obtained by PINN and FEM for problem (4)-(8)

Type of error	Error value (13900 epoch)	Error value (6000 epoch)	Error value (3000 epoch)
Mean square error	6.86e-06	5.12e-05	2.62e-05
Relative error in the l_∞norm	2.92 %	4.2 %	5.24 %
Relative error in the $l_2$norm	0.41 %	1.12 %	0.81 %

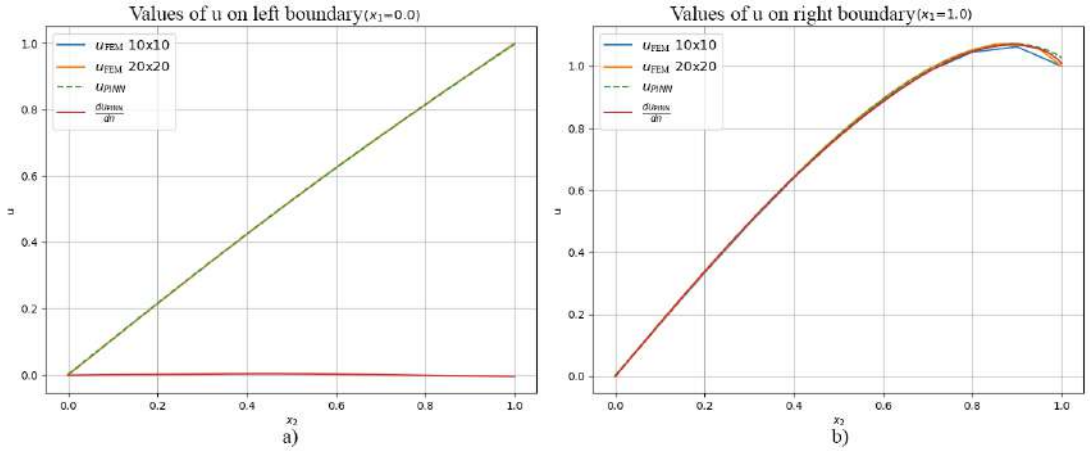

Figure 4: a) The approximate solution of (4)-(8) obtained by PINN and FEM for Γ_2. b) The approximate solution of (4)-(8) obtained by PINN and FEM for Γ_4.

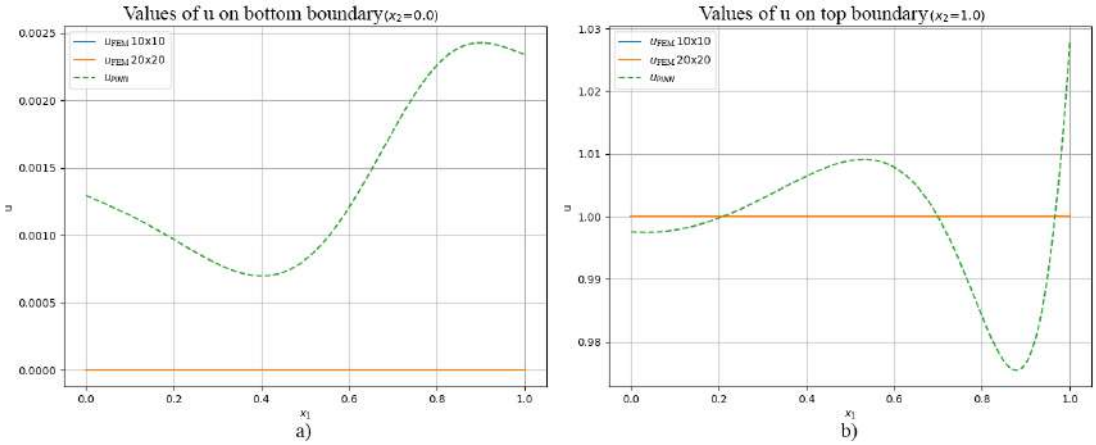

Figure 5: a) The approximate solution of (4)-(8) obtained using PINN and FEM for Γ_1. b) The approximate solution of (4)-(8) obtained using PINN and FEM for Γ_3.

4.2. Problem 2

Let us consider a one-dimensional non-stationary problem for the heat conduction equation:

$$\frac{\partial u}{\partial t}=\frac{\partial^2 u}{\partial x^2},(t,x)\in(0;0.2)\times(0;1), \tag{9}$$

$$u(0,t)=0, \tag{10}$$

$$u(1,t)=0, \tag{11}$$

$$u(x,0)=\sin(\pi x)-\sin(2\pi x)+\sin(3\pi x). \tag{12}$$

The analytical solution for (9)-(12) is obtained by applying the method of separation of variables:

$$u(x,t)=e^{-\pi^2 t}\sin(\pi x)-e^{-(2\pi)^2 t}\sin(2\pi x)+e^{-(3\pi)^2 t}\sin(3\pi x). \tag{13}$$

This neural network has 1981 parameters to train. Training of the PINN took 5 min 42 sec to achieve the loss given in Table 3. The average training time is 4 minutes and 17 seconds among the 5 training sessions. The deviation of the average time from the minimum time in the sample data is 77s, and from the maximum training time is 95s.

To balance the influence of different components of the loss function, the following coefficients were chosen in (2): for the initial condition (when $t=0$) $\lambda=5$, for the Dirichlet conditions on the left and right boundaries $\lambda=50$, and for the equation $\lambda=0.7$.

For the FEM, linear rectangular finite elements on a 25x25 grid were used.

Figure 8 and Figure 9 show that the approximate solution corresponds to the errors calculated in Table 4 (the error between the PINN and the analytical solution in the l_∞norm is 1.17 %). Figure 9 once again shows, that we approximate a line with the non-linear function in form of the neural network and will always get some deviations for approximating linear function. Also, in Table 4, we can see the error values for different numbers of epochs.

Figure 6 shows a graph of the loss function up to the final epoch, as well as from the 1000th to 3000th epoch. From Figure 6 a) after 4000 epoch small spikes of values of the loss functions are observed, as the optimizer tries to get out of local minimum to get closer to the global minimum. Figure 7 shows the approximate solution obtained by the PINN after 12441 training epochs.

Table 3

Selected hyperparameters of the neural network for the problem (9)-(12)

Learning speed	Nodes on one axis	Hidden layers	Number of neurons in one layer	Stopping criterion (loss)	Activation function
5e-4	25	3	30	2e-2	tanh

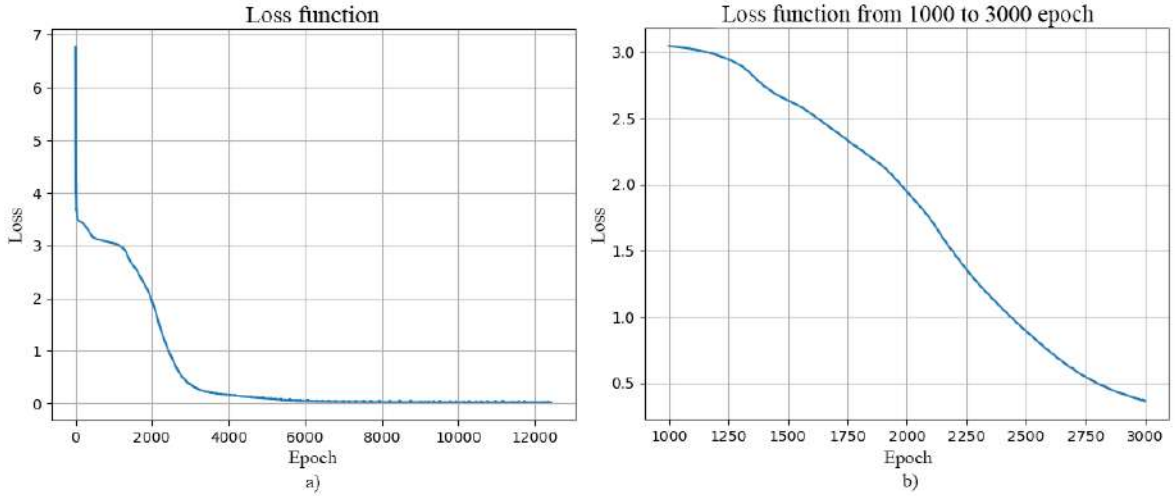

Figure 6: a) The loss over training epochs for the problem (9)-(12) up to the last 12441st epoch. b) The loss over training epochs for the problem (9)-(12) from the 1000th to 3000th epoch.

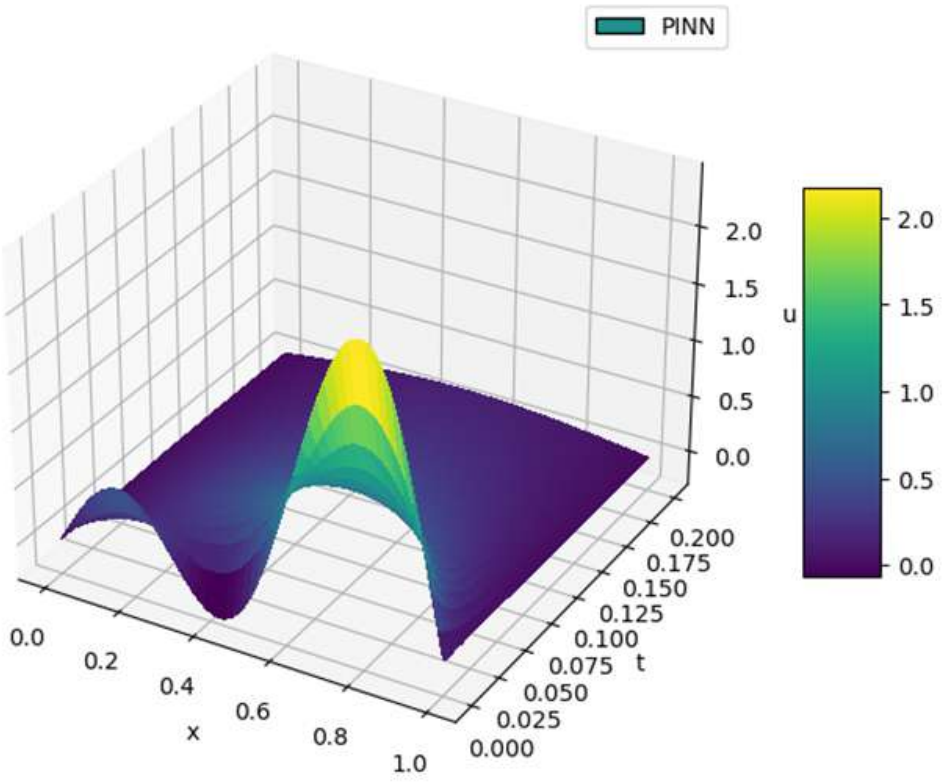

Figure 7: The approximate solution of (9)-(12) obtained by PINN after 12441 epochs.

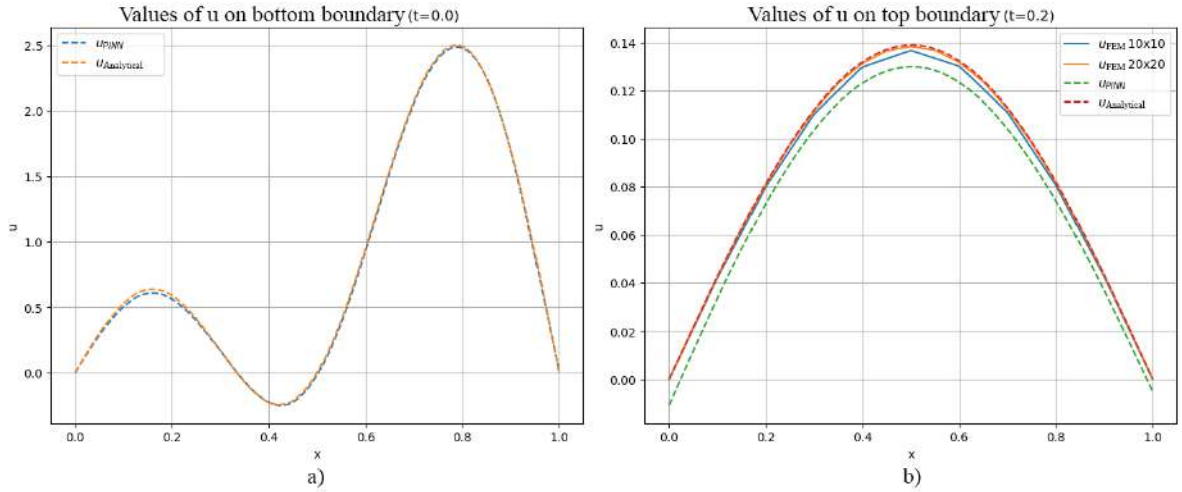

Figure 8: a) The approximate solution of (9)-(12) using PINN and the initial condition (12) at t=0. b) The approximate solution of (9)-(12) using PINN, FEM and the analytical solution at the final time t=0.2.

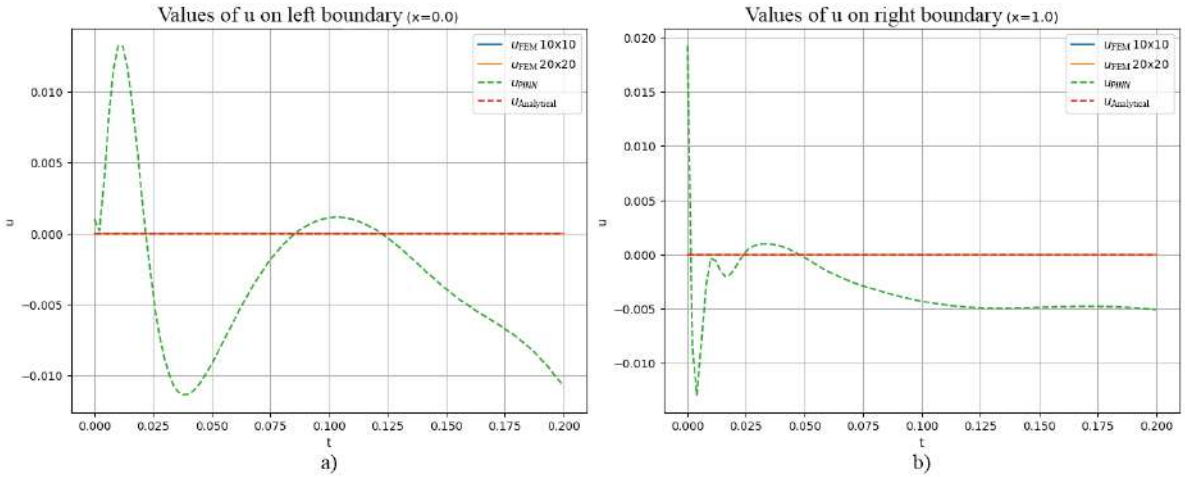

Figure 9: Figures a) and b) show the graphs of the approximate solution of (9)-(12) using PINN and FEM on the left and right boundaries.

Table 4
Error between the approximate solutions obtained by PINN and the analytical solution (13) for the problem (9)-(12)

Type of error	Error value (12441 epoch)	Error value (6000 epoch)	Error value (3000 epoch)
Mean square error	4.91e-05	5.4	1.81
Relative error in the l_∞norm	1.17 %	98.7 %	1e02 %
Relative error in the $l_2$norm	1.69 %	88.8 %	83.1 %

Table 5
Error between the approximate solutions obtained by PINN, FEM and the analytical solution (13) for the problem (9)-(12). Separate training session from results from Table 4

Type of error	PINN and FEM	PINN and analytical	FEM and analytical
Mean square error	6.43e-05	7.01e-05	1e-05
Relative error in the l_∞norm	1.72 %	1.72 %	1.07 %
Relative error in the $l_2$norm	1.95 %	2.03 %	0.76 %

The error trends presented in Table 4 show that longer training (more epochs) yields more accurate approximations, as seen by the decrease in mean square error with increased training. The relatively low error in the l_∞ norm (1.17 % at 12441 epochs) underscores the robustness of the PINN approach for this non-stationary heat conduction problem. Furthermore, the carefully chosen loss coefficients — particularly the higher weights for the boundary conditions — appear to contribute to the stable convergence of the solution. Moreover, Table 5 — presenting results from an independent training session that compares PINN with FEM and the analytical solution — shows that the relative errors are consistently low (approximately 1.72 % for PINN against both FEM and the analytical model and 1.07 % for FEM against the analytical solution). These results validate the effectiveness of PINN in capturing the dynamics of time-dependent problems while also highlighting the trade-off between training time and solution accuracy.

4.3. Problem 3

Definition. Let there be two closed connected domains $X, U \in R^2$ such that $X \subsetneq U$, $\partial X \varnothing \partial U = \varnothing$. Then, a doubly connected domain is a domain D such that: $D = \overline{U \setminus X}$.

Let $D \subset R^2$ be a limited doubly connected domain with sufficiently smooth boundaries Γ_1, $\Gamma_2 \in C^2$, whose parametric definitions are given by (14) and (15).

$$\Gamma_1 = \left\{ x_1(\varphi) = \left(2\cos(\varphi), 2\sin(\varphi)\right)\right), \varphi \in [0, 2\pi] \}, \tag{14}$$

$$\Gamma_2=\left\{x_2(\varphi)=\left(5\cos(\varphi),5\sin(\varphi)\right),\varphi\in[0,2\pi]\right\}. \quad (15)$$

Let us consider the problem of stationary heat conduction in a doubly connected domain D:

$$\Delta u=0 \text{ in } D \quad (16)$$

and boundary conditions

$$u=x \text{ on } \Gamma_1, \quad (17)$$

$$u=0 \text{ on } \Gamma_2. \quad (18)$$

This neural network has 1981 parameters to train. A pseudo-random number generator was used to generate the input data. The neural network was trained for 4 minutes and 20 seconds to achieve the losses given in Table 6.

To balance the influence of different components of the loss function, the following coefficients were chosen in (2): for the Dirichlet conditions on the left and right boundaries $\lambda=50$ and for the equation $\lambda=0.7$.

For the FEM, 197 linear triangular finite elements were used.

Figure 10 shows how the loss function decreases rapidly at the initial learning epochs. Figure 11 shows the approximate solution obtained by the PINN after 10611 training epochs. Graphs on the boundaries and errors for the entire domain for the last epoch and intermediate ones are shown in Figure 11 and Table 7, respectively. Figure 12 illustrates the values of the analytical solution and the approximate solution obtained by PINN after training and on intermediate epochs. As can be seen from the approximate solution in Figure 12 b) on intermediate epochs, u is approximated by a nonlinear function (NN consists of tanh activation functions and linear combinations), and the more we train NN, the closer it will get to a straight line, but will always contain some deviations.

Table 6

Selected hyperparameters of the neural network for the problem (16)-(18)

Learning speed	Number of internal points and on the border	Hidden layers	Number of neurons in one layer	Stopping criterion (loss)	Activation function
5e-4	500 and 50	3	30	1e-3	tanh

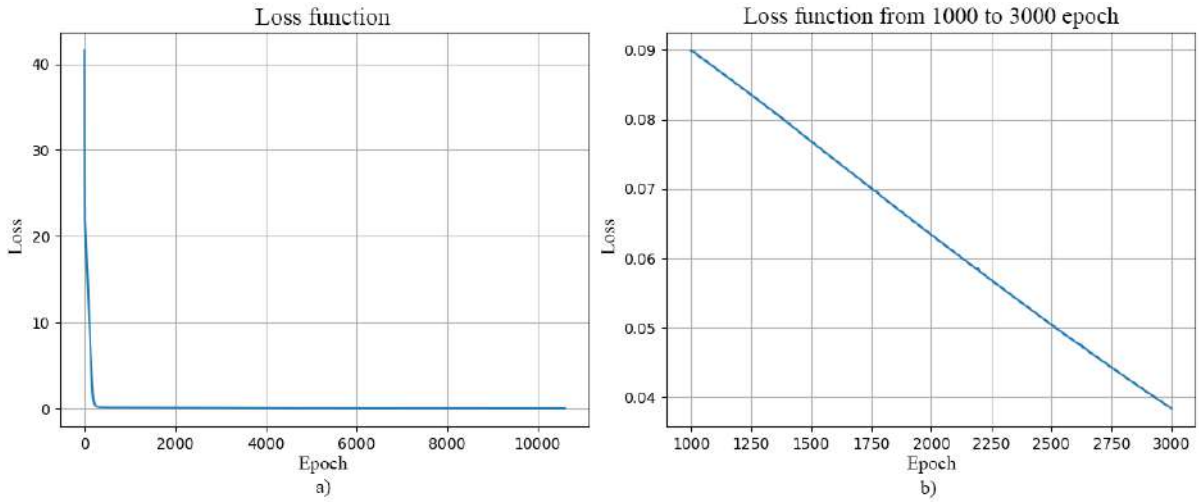

Figure 10: a) The loss over training epochs for the problem (16)-(18) up to the last 10611 epoch. b) The loss over training epochs for the problem (16)-(18) from the 1000th to 3000th epoch.

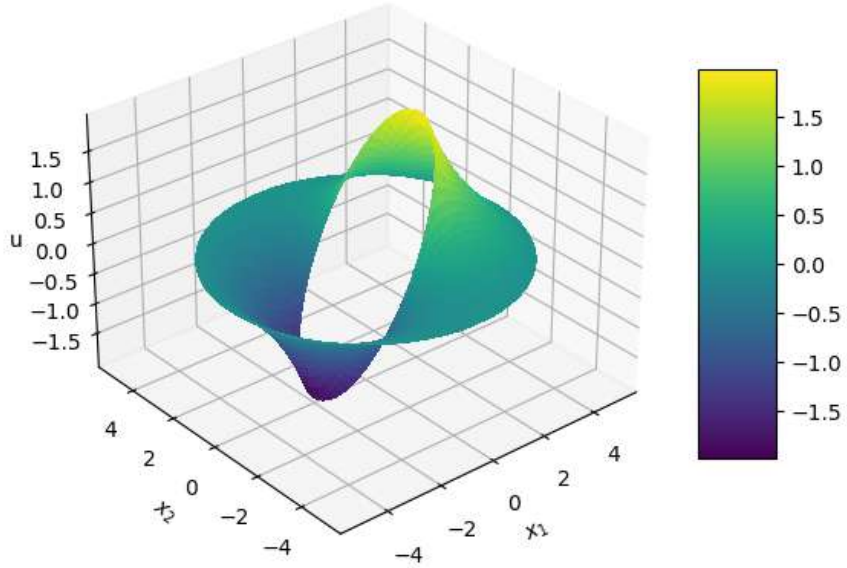

Figure 11: The approximate solution of (16)-(18) obtained by PINN after 10611 epochs.

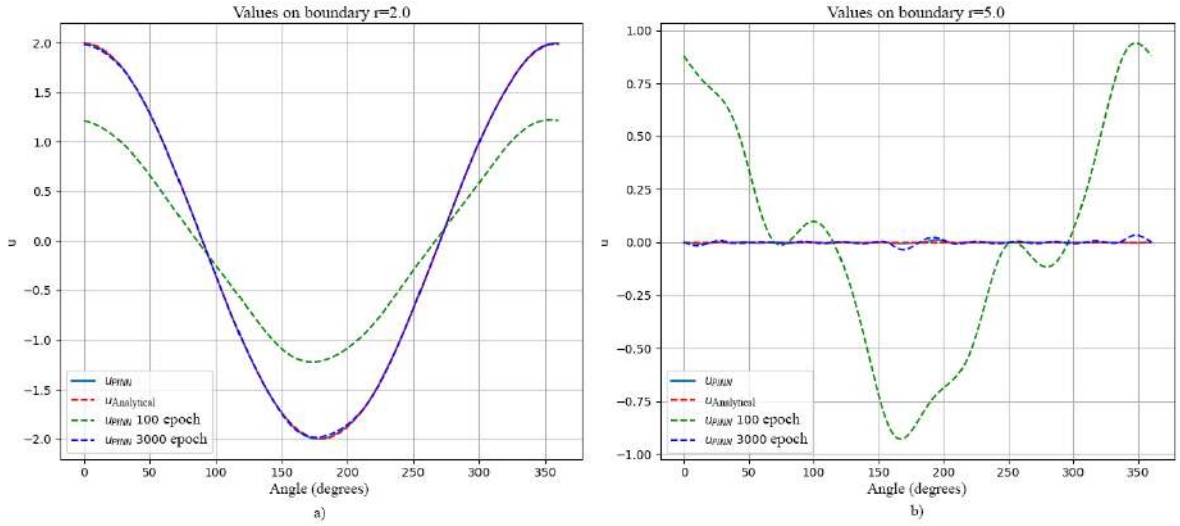

Figure 12: a) The approximate solution of (16)-(18) obtained by PINN (10611 epochs, 3000 epochs, 100 epochs) and the analytical value for Γ_1. b) The approximate solution of (16)-(18) obtained by PINN (10611 epochs, 3000 epochs, 100 epochs) and the analytical value for Γ_2.

Table 7
Error between the approximate solutions obtained by PINN and FEM solution for the problem (16)-(18)

Type of error	Error value (10611 epoch)	Error value (6000 epoch)	Error value (3000 epoch)
Mean square error	0.613	0.666	0.75
Relative error in the l_∞norm	2.26 %	9.54 %	77.4 %
Relative error in the $l_2$norm	1.95 %	10.2 %	63.8 %

The rapid decrease in loss during the early training epochs (as seen in Figure 10) demonstrates that the PINN quickly adapts to the challenges posed by the doubly connected domain. Despite the added complexity due to the domain geometry, the PINN achieves a competitive performance relative to the FEM approach, as indicated by the error metrics in Table 7. The gradual improvement in accuracy with extended training epochs underscores the importance of adequate training, especially for complex geometries. These results support the potential of PINNs for application in more intricate

heat conduction problems and suggest that further research into optimization strategies for training time reduction could yield even better performance.

5. Conclusions

This study set out to determine whether a compact feedforward PINN can reproduce finite-element (FEM) accuracy for linear, second-order parabolic and elliptic PDEs while accommodating mixed boundary conditions or non-rectangular geometries. For each problem: 2-D Laplace on a square, the same equation on a doubly-connected domain, and a 1-D non-stationary heat-conduction problem—the network depth and width were tuned empirically to minimize loss within a fixed training time. The resulting models achieved l_∞ errors of 2.92 %, 2.26 % and 1.17 %, respectively, after 4–6 minutes of training on an RTX 3080 Ti Laptop GPU, matching FEM accuracy while eliminating mesh generation and allowing rapid modification of governing equations or boundary conditions. Because time is treated as an additional input, the non-stationary case required no explicit time discretization scheme, further simplifying implementation. These results indicate that, for canonical diffusion problems in one and two dimensions with constant coefficients, a mesh-free PINN can match FEM accuracy when development flexibility outweighs computation time. These empirical results apply to the constant-coefficient cases we tested; however, convergence proofs [22] hold more generally for linear second-order parabolic and elliptic PDEs with Hölder-continuous (smooth) coefficients, so the theoretical foundation extends beyond the constant-coefficient setting.

The experiments also outline clear performance boundaries. Training remains markedly slower than FEM for comparable resolution, and optimization is sensitive to the relative weighting of interior, boundary and initial residuals. A broader survey of the literature shows that standard PINNs can struggle on more challenging PDEs: convergence proofs are still absent for nonlinear, stiff, high-frequency, or higher-order cases, and empirical work reports gradient-flow pathologies: vanishing, exploding, or mutually orthogonal gradients—that stall training and become more severe in higher spatial dimensions. Although our experiments focused on constant-coefficient diffusion problems, existing convergence theorems guarantee PINN convergence for any linear second-order parabolic or elliptic PDE with Hölder-continuous coefficients [22], and these theoretical and empirical findings together indicate that today's standard PINNs remain most reliable on modest-scale, well-conditioned diffusion examples.

Future research should slash training cost and enable high-dimensional scalability; extend PINNs to nonlinear, stiff, coupled, and stochastic PDEs; and rigorously validate their advantages on engineering and physical-science problems where meshing or classical solvers are prohibitive. Achieving these goals will elevate PINNs from promising prototypes to versatile, production-ready solvers.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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EfficientNet Deep Learning Model for Satellite Image Classification Using the EuroSAT Dataset

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Abstract

This study investigates the use of EfficientNet-B0, a computationally efficient convolutional neural network architecture, for satellite image classification using the EuroSAT dataset. Evaluating the baseline EfficientNet-B0 model, we achieved 98.1% overall accuracy and a 0.98 macro-averaged F1 score on the test set. This performance is highly competitive with state-of-the-art results reported for the EuroSAT dataset, demonstrating that EfficientNet-B0 offers a strong balance between high accuracy and computational efficiency. These findings suggest that EfficientNet-B0 is a promising approach for tasks requiring efficient satellite image categorization, such as large-scale land use monitoring, urban planning, and environmental management analysis based on satellite imagery.

Keywords
Satellite Image Classification, EfficientNet, Deep Learning, EuroSAT, Remote Sensing

1. Introduction

The Earth is composed of only about 29% land-continents and islands, and the remaining 71% is covered by water-saltwater bodies like oceans and seas as well as freshwater sources such as rivers or lakes: with 2% being made up by frozen forms such as ice caps or glaciers. Among the different types of lands, habitable land is the only one where one can live and produce things from it for example agricultural land which occupies about 70% pastureland and 30% arable land. Pasture, grazing land, rangelands, and meadows are primarily used for livestock rearing, whereas cultivated, arable, and croplands are designated for crop production. Manual classification of these various areas requires more time through image interpretation techniques [1] because localization costs too much money since data analysts don't want to do much digging around, so automation becomes necessary. This therefore calls for an effective automatic satellite image classification technique that involves learning different vegetation types e.g., agriculture, forests, etc., and studying urban-residential as well as commercial to determine different land uses in an area [2][3].

The significance of image interpretation from satellites has multiplied in different areas such as planning urbanization, agriculture and environmental monitoring. The demand for efficient and accurate ways of classifying this type of information is increasing in the face of ballooning satellite data volumes and improved quality. In urban planning, classification of satellite images helps create maps that highlight city configurations, debt infrastructure progress, or reveal land use patterns. Such knowledge helps to make informed choices concerning the allocation of resources and development needs for urban expansion. In addition, the agricultural sector uses these images to determine crop types variation, monitor their health conditions, note land cover changes among others which are useful in precision farming and management of crops. Furthermore, deforestation; desertification; water bodies alterations detection and analyses can be done through environmental monitoring based on these classifications. With an advancement in satellite technology comes a deeper richer data requiring sophisticated algorithms as well as machine learning techniques in order to manage these great volumes of information obtained.

Satellite imagery is a global effort to map worldwide communities such as OpenStreetMap [4], Google Earth [5], and Earth Explorer [6] which are platforms where maps are digitized using high-

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resolution images. These digitized maps act as living documents, where new features are added remotely by mappers located miles away while satellite pictures remain accessible to scientists across continents. Researchers have worked with various satellite image classification datasets like Landsat [7], Sentinel-2 [8], In-orbit [9], and RSI-CB256 [10] among others. Satellite imagery has a wide range of applications namely cartography and navigation [11], disaster response [12], and ecological monitoring [13]. These purposes can be achieved through highly accurate model satellite images.

This study investigates the use of EfficientNet, a state-of-the-art convolutional neural network architecture for classifying satellite images. In 2019, Tan and Le [14] developed an extremely effective image classification method known as EfficientNet which has been applied in many other fields too because it achieves excellent results while keeping computations at minimal levels. It is possible to make networks deeper, wider, or higher resolution through their compound scaling techniques, thus increasing both accuracy and efficiency beyond what traditional CNNs offer.

For this study, we utilize the EuroSAT dataset [15], a valuable resource for satellite image classification tasks. Recognizing the increasing need for methods that balance accuracy with computational efficiency in large-scale remote sensing, this research specifically evaluates the performance of the baseline EfficientNet-B0 architecture. By leveraging the EuroSAT dataset, we aim to establish a robust performance benchmark for EfficientNet-B0, assessing its ability to accurately classify diverse land use and land cover categories while capitalizing on its inherent efficiency. This evaluation helps determine its suitability for practical applications like land use monitoring and management strategies where both accuracy and processing speed are important considerations.

2. Related Works

With advances in satellite imaging and machine learning, land use and land cover (LULC) classification has made significant progress. LULC data is crucial for various applications, including urban planning, agriculture, forestry, and disaster management. Traditionally, LULC classification has relied on manual or semi-automatic methods that are time-consuming and prone to errors [16]. The integration of deep learning methods has improved both the efficiency and accuracy of classification tasks, enabling the analysis of large datasets [17].

The development of benchmark datasets has played a key role in advancing machine learning and computer vision research in remote sensing. Notable datasets such as the UC Merced Land Use Dataset [18] and BigEarthNet [19] have provided standardized benchmarks for training and evaluating models. These datasets have facilitated the comparison of algorithms, fostering innovation and progress in the field.

The EuroSAT dataset [15], is a benchmark dataset specifically designed for LULC classification tasks. EuroSAT has been widely used in various research contexts. Several papers have investigated alternative deep learning approaches. Yassine et al. [20] improved LULC classification from satellite imagery using deep learning techniques on the EuroSAT dataset, although they did not specify the architecture used. Similarly, Gunen [21] compared deep learning and machine learning methods for wetland water area determination using EuroSAT, highlighting the potential of deep learning but not focusing on a particular efficient architecture.

Kumari and Minz [22] explored the use of convolutional networks with focal loss optimization for LULC scene classification, also using the EuroSAT and Sentinel-2 datasets. Their work, however, differs from ours in its focus on loss function optimization rather than architectural efficiency.

Bhatt and Bhatt [23] proposed a novel methodology (DCRFF-LHRF) for efficient land cover classification on the EuroSAT dataset; however, their approach differs from ours in its methodological innovation rather than its specific choice of architecture.

Other research has focused on enhancing the EuroSAT dataset or exploring transfer learning techniques. Kunwar and Ferdush [24] investigated the application of transfer learning for LULC mapping using the EuroSAT dataset. Kurian et al. [25] similarly explored transfer learning approaches in remote sensing image classification, but without specific application to EuroSAT or a comparative study of various deep learning architectures. Gurav et al. [26] compared GAN-based methods for enhancing EuroSAT image classification, providing a complementary approach to improve classification accuracy.

The work by Honegger et al. [27] presented the EuroSAT Model Zoo, a valuable benchmark, but did not directly compare the performance of EfficientNet. Finally, while Ghozatlou et al. [28] explored

active learning for Earth observation satellite image classification, their focus on active learning strategies contrasts with the focus of this study on the efficient architecture of EfficientNet.

This study distinguishes itself by providing a focused evaluation of the baseline EfficientNet-B0 variant's performance specifically on the EuroSAT dataset, analyzing its effectiveness in terms of both classification accuracy and its inherent computational efficiency. While previous works have applied various deep learning models [20-23, 27, 28] or transfer learning approaches [24, 25] to EuroSAT, or explored different aspects like loss functions [22] or data enhancement [26], few have systematically benchmarked the trade-offs offered by the lightweight, entry-level EfficientNet-B0. By establishing this performance baseline, our work provides a valuable reference point for assessing the practical utility of efficient architectures and for comparison against future, potentially more complex models developed for EuroSAT-based land cover classification.

3. Proposed Methodology

3.1. Dataset

The dataset, that used in the study, includes various categories such as annual crop, forest, herbaceous vegetation, motorway, industrial, pasture, permanent crop, residential, river, sea, and lake. The EuroSAT dataset is particularly suitable for this study due to its comprehensive coverage of European land cover types and its multispectral nature. This allows to evaluate the performance of EfficientNet on a variety of satellite imagery that closely mimics real-world applications. Furthermore, the balanced class distribution of the dataset allows a fair assessment of the classification capabilities of the model across different land use categories. EuroSAT consists of 27,000 labeled Sentinel-2 satellite images covering 13 spectral bands and 10 land use and land cover classes. The images are 64x64 pixels in size. Each class contains 2,000 to 3,000 images. Figure 1 shows the distribution of images in the dataset by class. Figure 2 provides examples of the dataset.

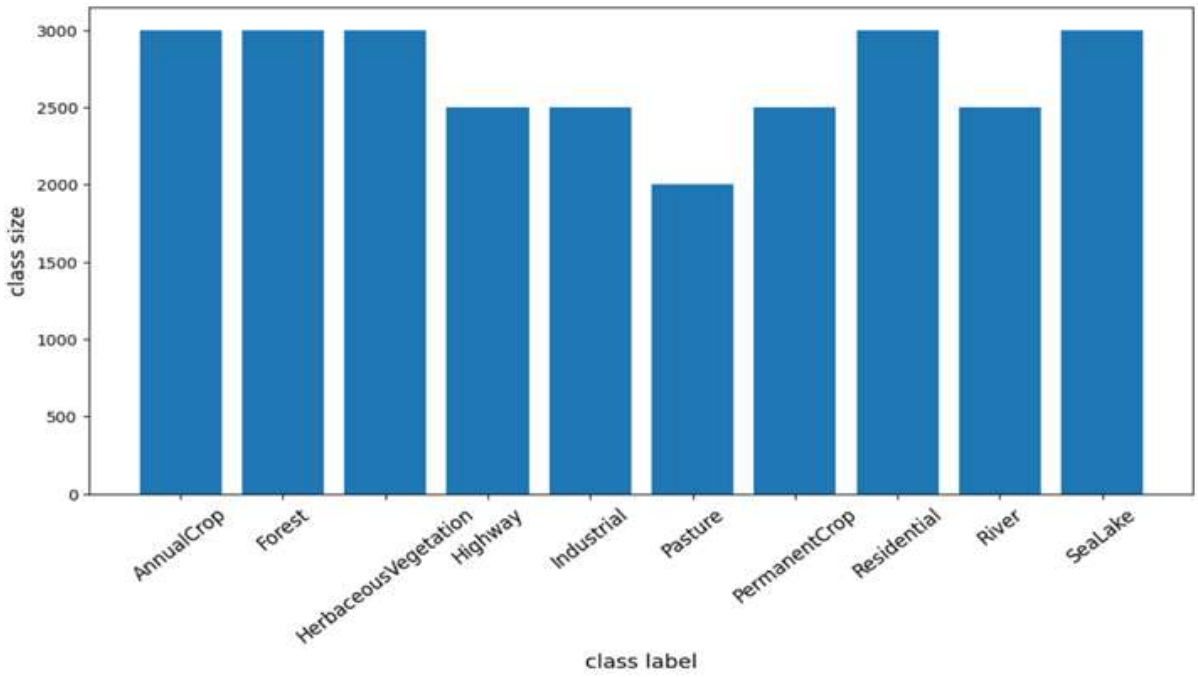

Figure 1: Distribution of images per class

Figure 2: Samples of The EuroSAT Dataset [15]

The EuroSAT is a dataset of satellite imagery selected in relation to the cities covered in the European Urban Atlas. The cities covered are distributed over 34 European countries: Austria, Belarus, Belgium, Bulgaria, Cyprus, Czech Republic (Czechia), Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy/Holy See, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Republic of Moldova, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine and the United Kingdom. The distribution of the EuroSAT dataset is shown in Figure 3.

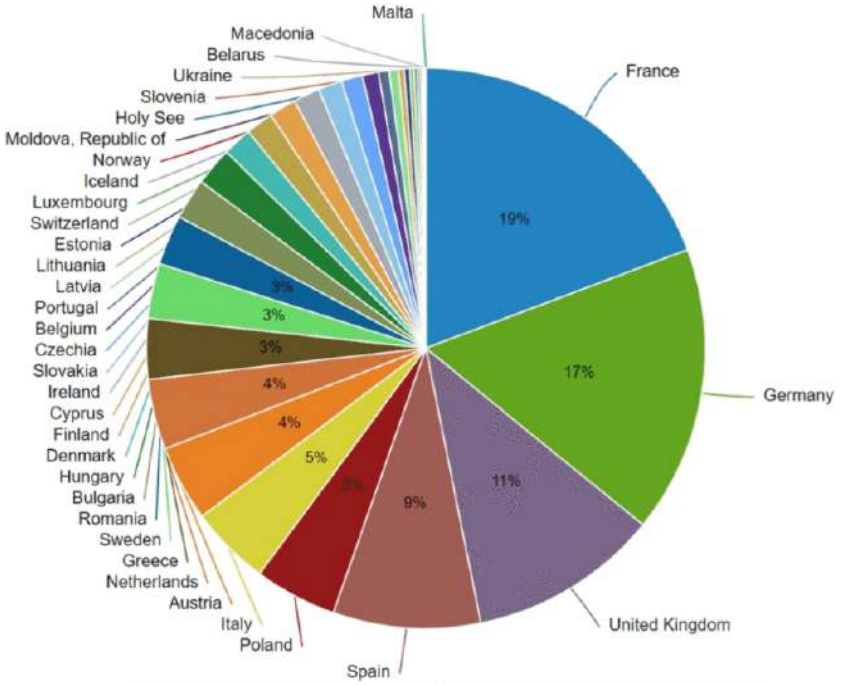

Figure 3: EuroSAT dataset distribution.[15]

The illustration in Figure 4 gives an overview of the process of patch-based land use and land cover classification using satellite imagery. A satellite scans the Earth's surface to collect images from the ground. From these images, small-sized image patches are used for the classification task. The aim is to automatically provide labels that identify the physical type of terrain or how the land is used. To do this, an image patch is fed into a classifier, in this case a neural network, and the classifier predicts the class shown on the image patch.

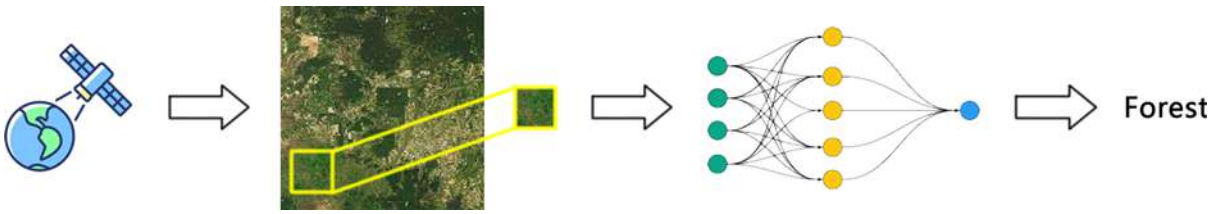

Figure 4: Overview of the use of the EuroSAT dataset in the study

3.2. EfficientNet

In this study, EfficientNet-B0 was selected as the primary model for classifying satellite images. As the baseline architecture within the EfficientNet series [14], it is specifically designed to optimize the balance between model complexity (depth, width, resolution) and performance effectively [29]. Our rationale for choosing B0 was to first establish a performance benchmark using the most computationally efficient member of this model family, providing insights into its suitability for resource-aware applications before potentially exploring larger, more computationally intensive variants. These networks rely on mobile inverted bottleneck convolution (MBConv) as their fundamental building blocks. MBConv incorporates a technique known as squeezing-and-excitation optimization. This method enhances the model's ability to recalibrate feature channels, thereby improving its overall performance in classification tasks.

EfficientNet-B0 uses activation functions that contribute to its efficiency. The model also includes depth-wise separable convolutions, allowing for reduced computational costs during training. This feature is particularly beneficial when handling large datasets, like satellite images. The model comprises seven distinct stages, each containing a varying number of layers, specifically between one and four layers, depending on the requirements of the stage.

The input layer of EfficientNet-B0 was adapted to suit the satellite image classification task effectively. This adaptation was necessary to accommodate the 13 spectral bands utilized in the EuroSAT dataset [30]. These bands represent different wavelengths of light, providing important information for land classification.

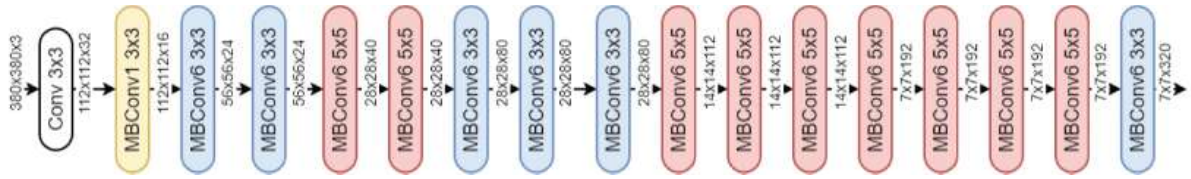

Figure 5: The architecture of EfficientNet b0[31]

At the end, the final classification layer is replaced by a new fully connected layer with ten output nodes corresponding to land use and land cover classes from the dataset. These nodes correspond to the specific land use and land cover classes defined in our dataset. This adjustment ensures that the model accurately reflects the categories to aim to classify. The initial weights of the model were set using pre-trained weights from ImageNet, a large and diverse image dataset. This process took advantage of transfer learning, allowing the model to adopt to the unique characteristics of the satellite images while retaining the knowledge gained from the ImageNet dataset. This strategic approach set the foundation for our satellite image classification efforts. Figure 5 provides an example structure of the model used in this study.

4. Experimental Results

The baseline model called EfficientNet-B0, achieved an overall accuracy of 98.1% on the EuroSAT test set. It demonstrates that EfficientNet is efficient for satellite image classification tasks, performing at a competitive level with state-of-the-art results on this dataset. At the end of training, loss, and accuracy graphs were obtained. These graphs are shown in Figure 6. The plot of loss reveals a significant drop-off of both train and validation losses across epochs as it gradually declines from initial high values. This trend shows good convergence, while the closeness between training and validation losses indicates that the model generalizes well without any symptoms of overfitting. The accuracy plot shows a clear upward trend with accuracy peaking above 90%. This means that as the model trains, its predictions

become more accurate over time. The steady improvement implies that further training could yield more benefits. Thus, these results prove that the model learns very well and generalizes effectively when applied to satellite image data.

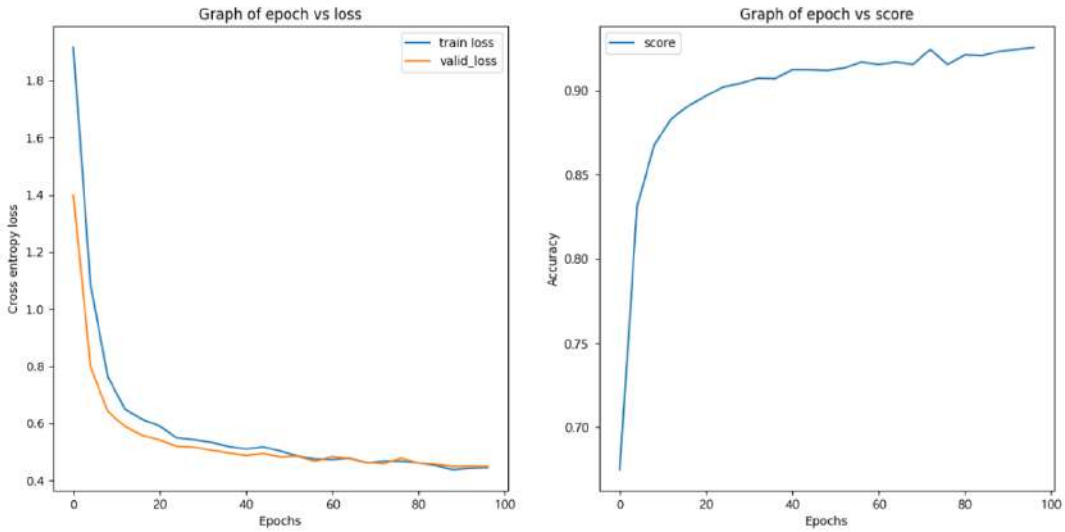

Figure 6: Loss and Accuracy graphs

The EfficientNet-B0 model showed strong performance on all 10-land use and land cover categories in the EuroSAT dataset, with F1-scores ranging from 0.96 to 1.00. The model excels in classifying different categories such as "PermanentCrop" and "River" due to their unique spectral signatures and homogeneous textures in satellite imagery. Classes such as "AnnualCrop", "Highway" and "SeaLake" also performed well with F1-scores of 0.99. The results for each class are shown in Table 1.

Table 1
Test Results

Class	Precision	Recall	F1 Score
AnnualCrop	0.99	0.99	0.99
Forest	0.96	0.98	0.97
HerbaceousVegetation	0.98	0.96	0.97
Highway	1.00	0.99	0.99
Industrial	0.97	0.96	0.96
Pasture	0.96	0.98	0.97
PermanentCrop	1.00	1.00	1.00
Residential	0.98	0.95	0.96
River	1.00	1.00	1.00
SeaLake	0.98	0.99	0.99

In Figure 7, the confusion matrix shows the classification performance of the EfficientNet B0 model on satellite images. The highest value along diagonal represents perfect accuracies with AnnualCrop, highway and permanent crops being particularly strong at; 0.99, 0.99 and 1.00 respectively. Thus, these values imply that a large number of these categories are correctly classified by this model with high precision. However, there is slight confusion, such as Forest being misclassified as Herbaceous Vegetation (1% of Forest samples) and Residential areas sometimes misclassified as SeaLake (3% of Residential samples). This suggests the model faces slight difficulties distinguishing between categories with potentially similar spectral characteristics (e.g., certain forest types vs. dense vegetation) or contextual elements (e.g., coastal residential zones, properties with large water features). Overall, the matrix demonstrates strong performance while highlighting specific areas where future work might yield improvements.

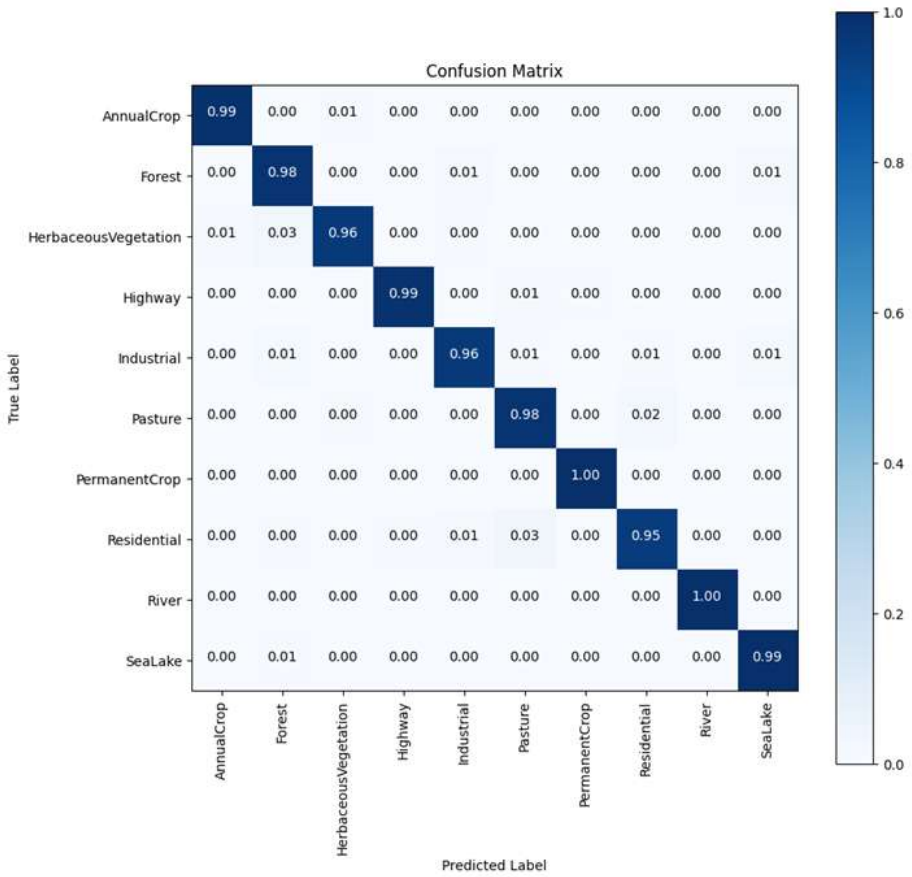

Figure 7: Confusion Matrix

5. Discussion

The experimental results clearly demonstrate that EfficientNet-B0 is a highly effective model for satellite image classification using the EuroSAT dataset. Achieving 98.1% overall accuracy and a 0.98 macro-averaged F1 score, its performance is competitive with, or exceeds, several reported state-of-the-art methods on EuroSAT, validating its capability. The performance across different classes was consistently high, with F1-scores ranging from 0.96 to 1.00, highlighting its robustness in distinguishing different landscape types.

One of the key advantages of EfficientNet-B0 is its computational efficiency, which is particularly relevant in remote sensing applications where handling large-scale satellite imagery is essential. The compound scaling approach of EfficientNet allows it to balance model depth, width, and resolution while maintaining strong performance. This efficiency, combined with the demonstrated high accuracy, makes it a compelling baseline, particularly for applications where computational resources may be constrained.

The confusion matrix analysis indicates that the model performs well across most categories, with particularly strong classification in classes such as PermanentCrop and River, likely due to their distinct spectral signatures. However, minor misclassifications were observed between Forest and Herbaceous Vegetation, as well as between Residential and SeaLake. These errors, potentially stemming from spectral similarities or contextual overlaps as noted in Section 4, and possibly influenced by the dataset's resolution, indicate areas for potential improvement. Future work could address these challenges by incorporating additional training data, fine-tuning hyperparameters, or leveraging ensemble learning techniques to further improve classification accuracy.

Additionally, while EfficientNet-B0 has proven to be a powerful and efficient baseline model, exploring other EfficientNet variants (such as B3 or B4) which trade some efficiency for potentially higher capacity [14], or applying advanced transfer learning techniques, could further enhance performance. Multi-spectral feature fusion, integrating different spectral bands from Sentinel-2, may also improve class separability, especially for challenging categories.

Overall, the findings suggest that EfficientNet is a promising architecture for satellite image classification, offering a balance between accuracy and computational efficiency. The results indicate their potential for large-scale automated remote sensing applications, paving the way for more efficient and accurate land cover monitoring in the future.

6. Limitations and Future Work

While this study demonstrates the effectiveness of EfficientNet-B0 for satellite image classification using the EuroSAT dataset, it is important to acknowledge certain limitations and potential avenues for future research. Understanding these limitations is crucial for interpreting the results within a broader context and guiding future efforts to improve the accuracy and applicability of satellite image classification techniques.

6.1. Dataset-Related Limitations

The EuroSAT dataset, while widely used and valuable, presents certain inherent limitations. The images are relatively low-resolution (64x64 pixels), which may limit the ability to distinguish fine-grained details and complex land cover patterns. This lower resolution may result in difficulties in classifying urban areas with dense buildings or agricultural areas with narrow fields, for example. Furthermore, EuroSAT represents a specific geographic region (Europe) and period. This may limit the generalizability of the trained model to other regions with different environmental conditions, agricultural practices, or land use patterns. The dataset's class balance, while generally good, may not perfectly reflect the real-world distribution of land cover types in all regions, potentially leading to biased performance in specific applications. Another aspect to consider is the reliance on Sentinel-2 imagery alone. Integrating other data sources, such as LiDAR data for elevation information or radar data for cloud penetration, could provide complementary information and improve classification accuracy, especially in cloud-prone regions.

6.2. Model-Related Limitations

EfficientNet-B0, while computationally efficient, is a relatively shallow model compared to some other deep learning architectures. More complex models, such as larger EfficientNet variants (B1-B7) or transformer-based models, may potentially achieve higher accuracy, especially on more challenging datasets or with higher-resolution imagery. However, increasing model complexity typically comes at the cost of increased computational requirements and a greater risk of overfitting, requiring careful regularization and validation strategies. The reliance on ImageNet pre-trained weights, while beneficial for transfer learning, may also introduce a bias towards features that are more common in natural images than in satellite imagery. Fine-tuning the model with a larger satellite-specific dataset or exploring alternative pre-training strategies could potentially mitigate this bias. Also, the current implementation does not explicitly address the spatial context of the images. Integrating spatial information, such as using contextual information from neighboring image patches, could improve classification accuracy, especially for land cover types that exhibit spatial dependencies (e.g., agricultural fields or urban areas).

6.3. Future Research Directions

Building upon the success of this study, several exciting avenues for future research emerge. A primary focus should be on expanding the datasets utilized in model training, incorporating larger, more diverse, and higher-resolution satellite imagery from various geographic regions. This could also involve leveraging multi-temporal data to capture seasonal variations and fusing data from multiple sensors like LiDAR and radar to enhance classification accuracy, particularly in cloud-prone areas. Moreover, exploring more advanced deep learning architectures, such as transformer-based models or hybrid CNN-transformer networks, holds the potential for improved performance by capturing long-range dependencies and contextual information more effectively. Developing domain-specific pre-training strategies tailored to satellite imagery characteristics, rather than relying solely on ImageNet pre-trained weights, could further enhance feature extraction. Addressing the challenges of uncertainty and explainability in model predictions is crucial, necessitating the

development of methods for quantifying and visualizing prediction uncertainties, as well as exploring explainable AI techniques to understand model decision-making processes. Furthermore, focusing on real-world applications and deployment in areas like land use monitoring and urban planning is essential, involving the creation of user-friendly tools and integration of models into existing workflows. Finally, exploring active learning strategies to reduce the need for vast labeled datasets and utilizing temporal analysis to detect land cover changes over time represents promising avenues for future investigation. By pursuing these directions, the field of satellite image classification can continue to advance, ultimately leading to more sustainable and effective management of our planet's resources.

7. Conclusion

EfficientNet-B0 has emerged as a highly compelling solution for satellite image classification when applied to the EuroSAT dataset. Achieving a robust overall accuracy of 98.1% and a macro-averaged F1 score of 0.98, the model demonstrates a strong capacity to effectively categorize ten distinct land use and land cover classes. This level of performance is comparable to state-of-the-art results reported in the literature for this dataset, establishing EfficientNet-B0 as a strong baseline contender. The consistently high F1-scores across the different classes, ranging from 0.96 to 1.00, further emphasize its reliability and potential for broad applicability in real-world scenarios where diverse landscapes are encountered. The observed reduction in training and validation losses throughout the training process reinforces the model's ability to generalize well and minimize misclassifications, indicating a robust learning process.

Beyond the accuracy metrics, the inherent computational efficiency of EfficientNet-B0 is a significant advantage. This efficiency allows for the processing of large-scale satellite imagery datasets without demanding excessive computational resources, a critical factor for practical deployment in operational settings. The model's ability to balance accuracy with computational cost makes it a valuable tool for applications where timely and cost-effective analysis is paramount.

The detailed confusion matrix analysis provides valuable insights into the model's performance, highlighting areas of strength and potential areas for refinement. While the model exhibits excellent performance, minor misclassifications between spectrally similar classes suggest areas for future refinement, potentially through strategies like incorporating additional data or multi-spectral fusion, as discussed. Exploring larger EfficientNet variants or more recent architectures may also yield improvements, likely with increased computational demands.

Looking forward, future research should focus on several key areas to further enhance the model's performance and broaden its applicability. First, addressing the observed misclassifications through strategies such as incorporating additional training data, especially for the less well-classified categories, could prove beneficial. Further optimization of the model's architecture, including fine-tuning hyperparameters specific to satellite imagery characteristics, may also yield improved results. Exploring alternative EfficientNet variants, such as B1, B3, or B4, or even experimenting with more recent architectures, could lead to increased accuracy, potentially at the expense of some computational efficiency. Furthermore, incorporating multi-spectral feature fusion techniques, leveraging the rich spectral information from the Sentinel-2 bands, could improve class separability and reduce ambiguity in classification, especially for the challenging land cover types. The use of data augmentation techniques could also be explored to improve model generalization and robustness.

In conclusion, this study validates EfficientNet-B0 as a powerful and efficient solution for satellite image classification on EuroSAT. The demonstrated performance, combined with identified avenues for future research, positions EfficientNet-based approaches as a promising pathway toward advanced and automated remote sensing capabilities, contributing valuable insights for the effective and sustainable management of our planet's resources.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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Evolving Neo-Fuzzy System with Adaptive Learning for Online Forecasting of Non-stationary Processes

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Abstract

This research focuses on developing an evolutionary neo-fuzzy system for online learning of non-stationary processes. During the study, structural and functional schemes of the system were designed and substantiated. Epanechnikov kernels were proposed as membership functions. Experimental verification of the developed approach demonstrated its effectiveness for forecasting problems under conditions of uncertainty.

Keywords

time series forecasting; data preprocessing; neural networks; online mode; Epanechnikov kernels

1. Introduction

The problem of mathematical forecasting of time series data has been well studied. Today, there is a vast number of publications dedicated to this topic, including both theoretical works and practical studies aimed at solving applied problems. Currently, there are many time series forecasting methods, ranging from the simplest, such as regression, correlation, spectral, and exponential smoothing, to more advanced intelligent methods that sometimes rely on rather complex mathematical frameworks [1,2]. The forecasting task becomes significantly more complicated if the analyzed sequences contain trends of an a priori unknown nature, are nonlinear and non-stationary, and include quasi-periodic components, stochastic and chaotic elements, anomalous outliers, and sudden trend jumps. In such situations, nonlinear predictors based on computational intelligence techniques, particularly neuro-fuzzy systems [3–5], have proven highly effective due to their strong approximation and extrapolation capabilities and ability to adjust parameters based on training data, which is typically given a priori. At the same time, it is assumed that the structure of such a neuro-fuzzy predictor is predefined and does not change during operation and forecasting. The situation becomes significantly more complex when data is received sequentially at a high frequency in the form of a stream, and there is no predefined training set. At the same time the internal structure of the analyzed sequence is a priori unknown and may change over time. Additionally, the internal structure of the analyzed sequence is a priori unknown and may change over time [6,7]. This situation is considered within the theory of evolutionary computational intelligence systems.

Existing evolutionary systems, particularly neuro-fuzzy systems, are still not well adapted for real-time operation under conditions of significant non-stationarity [8–10]. The performance of a forecasting system can be improved by using the so-called neo-fuzzy approach instead of the traditional neuro-fuzzy approach, which has proven effective in time series forecasting tasks [3,11]. However, it was assumed that this sequence changes within a predefined range. At the same time, there is a relatively broad class of real-world processes, primarily in energy, medicine, finance, control, and moving object tracking, where determining the range of the analyzed signal a priori is problematic. This range, in turn, defines the placement of membership functions at the inputs of a neo-fuzzy system.

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Therefore, this work proposes an architecture and a fast adaptive learning algorithm for an evolutionary neo-fuzzy system for forecasting significantly non-stationary sequences, where the possible range of variation is a priori unknown, and data is processed sequentially online.

2. The architecture of forecasting neo-fuzzy system

As the basic architecture of the nonlinear predictor, it is convenient to use the so-called ANARX model (Additive Nonlinear Autoregressive with Exogenous inputs) [12], which has the form (1):

$$\hat{y}(k) = f_1(y(k-1), x(k-1)) + f_2(y(k-2), x(k-2)) + \ldots + f_n(y(k-n), x(k-n)) \quad (1)$$

and is a generalization to the nonlinear case of specific Box-Jenkins predictors.

Here $\hat{y}(k)$ is the forecast of the analyzed sequence at the current discrete time moment $k = 1, 2, \ldots$; $f_l(\cdot)$ is a specific nonlinear transformation, usually implemented either by an artificial neural network or a neuro-fuzzy system; $x(k)$ is an observed exogenous factor that determines the behavior of the analyzed sequence $y(k)$; $n = \max\{n_x, n_y\}$ is the model order.

The advantage of model (1) is that the general task of constructing a nonlinear adaptive predictor is decomposed into n subtasks of synthesizing two-input models, where the input signals are $y(k-l),\ x(k-l)$, $l = 1, 2, \ldots, n$, while the local predictors $f_l(y(k-l), x(k-l))$ can be adjusted independently of each other. Furthermore, the model order n can be conveniently adjusted directly in the learning (evolution) process.

Predicator (1) can be easily generalized to the case of multiple exogenous variables $x_1(k), x_2(k), \ldots, x_q(k)$, in which case such a multi-input predictor takes the form

$$\hat{y}(k) = \sum_{l=1}^{n} f_l(y(k-l), x_1(k-l), x_2(k-l), \ldots, x_q(k-l)) \quad (2)$$

,

where each of the local predictors $f_l(\cdot)$ has $q+1$ inputs.

In the case of data stream processing, when information arrives in online mode, the primary focus is on the speed of data processing and the simplicity of numerical implementation of the computational intelligence system. Instead of neural networks and neuro-fuzzy systems, which require significant computational resources for their training, it is advisable to use a neo-fuzzy approach [13], which is characterized by high learning speed, computational simplicity, good approximation properties, and the ability to be tuned in an online mode with maximum possible speed. Figure 1 presents the scheme of a neo-fuzzy system designed for real-time prediction of non-stationary processes.

The first layer of the system consists of $2n$ delay elements (time delay) z^{-1}, which form the historical context of the predicted process $y(k-l),\ x(k-l)$. If the predictor structure (2) is used, then the number of delay elements is $(q+1)n$.

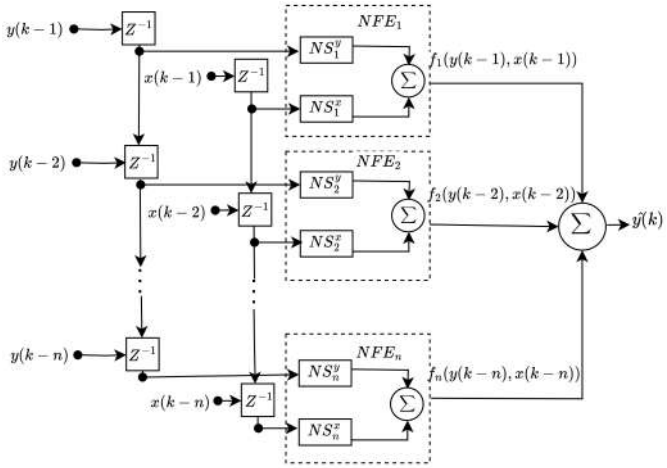


Figure 1: Neo-fuzzy system for non-stationary process forecasting

The second hidden layer consists of n neo-fuzzy elements NFE_l, each of which is essentially a neo-fuzzy neuron with two nonlinear synapses NS_l^y, NS_l^x (q+1 nonlinear synapses for the predictor (2)) and forms the forecast components $f_l(y(k-l), x(k-l))$. Finally, the output layer consists of a single summator, where the final prediction $\hat{y}(k)$ is computed.

The key elements of the system are the nonlinear synapses NS_l^y, NS_l^x, which directly solve the problem of approximating the historical data of the analyzed sequence. Figure 2 shows the structure of a neo-fuzzy element NFE_l, which consists of two nonlinear synapses. However, it is important to note that for the predictor (2), each neo-fuzzy element contains q+1 nonlinear synapses.

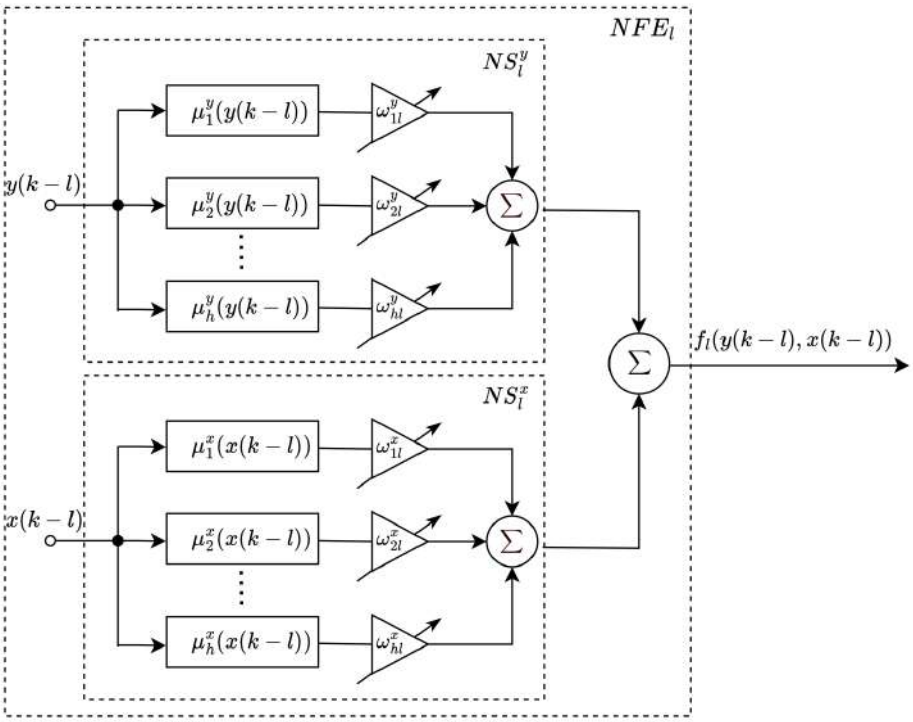


Figure 2: Neo-fuzzy element with two nonlinear synapses

It is important to note that each nonlinear synapse essentially performs an F-transform in an adaptive form [14, 15], which makes it a universal approximator of the historical sequence.

Each of the nonlinear synapses NS_l^y, NS_l^x contains h membership functions $\mu_i^y(y(k-l)), \mu_i^x(y(k-l))$, where $i = 1, 2, ..., h$ as well as h adjustable synaptic weights w_{il}^y, w_{il}^x, which must be continuously updated during the processing of the predicted signal.

Upon receiving the input values $y(k-l), x(k-l)$ the output of NFE_l forms the value given by equation (3)

$$f_l(y(k-l), x(k-l)) = \sum_{i=1}^{h} w_{il}^y \mu_i^y(y(k-l)) + \sum_{i=1}^{h} w_{il}^x \mu_i^x(x(k-l)) \quad (3)$$

,

which is a component of the required forecast (4):

$$\hat{y}(k) = \sum_{l=1}^{n} f_l(y(k-l), x(k-l)) = \sum_{l=1}^{n} \left(\sum_{i=1}^{h} w_{il}^y \mu_i^y(y(k-l)) + \sum_{i=1}^{h} w_{il}^x \mu_i^x(x(k-l)) \right). \quad (4)$$

Triangular functions are typically used as membership functions in neo-fuzzy neurons, as they satisfy the conditions of unity partitioning (Ruspini partitioning). [16]. The advantage of triangular functions is that at each training step k, only two neighboring membership functions are activated, meaning that only $4n$ synaptic weights require adjustment, which simplifies the learning process. A drawback of these functions is that they allow only piecewise linear approximation, which reduces prediction accuracy. In [17], B-splines were used as membership functions, which improved

prediction accuracy but complicated the learning process, as at each discrete time step k, all $2nh$ weights required to be updated.

In our opinion, a reasonable compromise between these functions is the use of Epanechnikov kernels, which have proven to be highly effective in regression and pattern recognition tasks [18].

Figure 3 presents the system of membership functions of a nonlinear synapse based on Epanechnikov kernels:

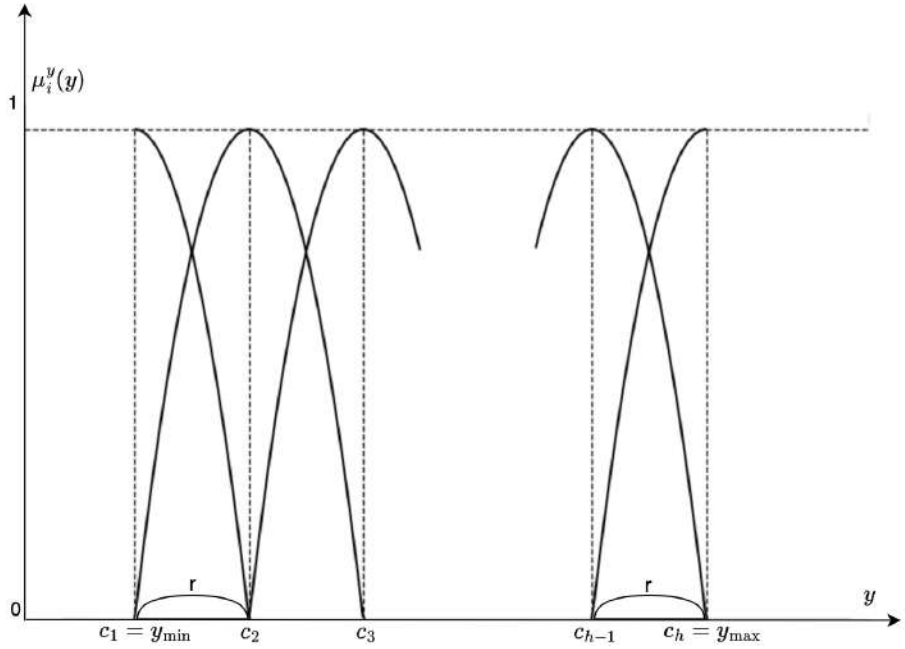


Figure 3: Epanechnikov kernels as membership functions

To construct this system, it is necessary to define the range of the controlled sequence and the number of these functions, which is usually chosen based on purely empirical considerations. The number of these functions does not affect the learning process, as only two neighboring functions $\mu_i^y(y(k)), \mu_{i+1}^y(y(k))$ are activated at any moment. The distance between the extrema of two neighboring functions is determined as shown in equation (5):

$$r = \frac{y_{\max} - y_{\min}}{h-1}. \tag{5}$$

The functions themselves can be expressed as equation (6):

$$\mu_i(y) = \left(1 - \frac{(y-c_i)^2}{r^2}\right)\delta_i = \left[1 - \frac{(y-c_i)^2}{r^2}\right]_+, \tag{6}$$

where $\delta_i = \begin{cases} 1, \text{ if } |y - c_i| < r, \\ 0, \text{ otherwise}, \end{cases}$, $[y]_+ = \max\{0, y\}$.

3. Adaptive learning of the predictive neo-fuzzy system

The placement of membership functions in nonlinear synapses NS_i^y, NS_i^x significantly depends on the a priori defined boundary values $y_{\min}$, $y_{\max}$, $x_{\min}$, $x_{\max}$, which are usually determined based on purely empirical considerations. When forecasting non-stationary sequences, sudden signal jumps and the emergence of rapidly increasing and decreasing trends that extend beyond the predefined range $[y_{\min}, y_{\max}]$ may occur. Of course, it would be possible to set a sufficiently wide range initially, but this would lead to a significant increase in the number of membership functions and adjustable synaptic weights, making the system excessively complex. We believe that this problem can be addressed by leveraging ideas from evolutionary systems, where not only synaptic weights but also the system's architecture are adjusted during the learning process. Reconfiguring the architecture in

real time is quite challenging; therefore, it is advisable to limit modifications to the evolution of the membership function system while preserving their number and the number of synaptic weights. Suppose that at a specific moment in time, the predicted sequence takes a value $y^*_{\max} > c_h$, as shown in Figure 4.

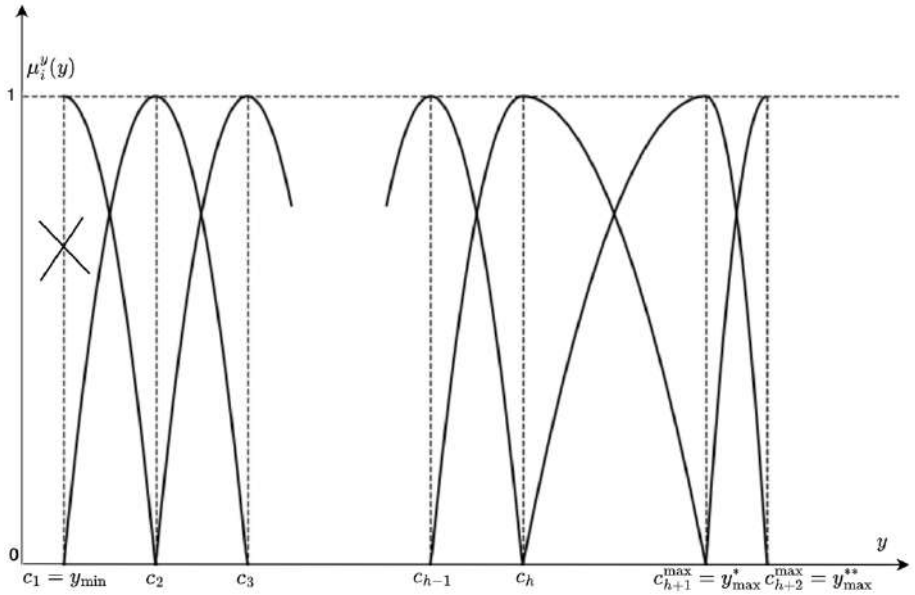


Figure 4: Evolution of the membership function system when $y^*_{\max} > c_h$

Based on this value, a new membership function is formed with the center $c_{h+1}^{\max} = y^*_{\max}$, and the function becomes asymmetric, meaning that (7) holds:

$$\mu_{hL}^y(y) = \left[1 - \frac{(y - c_h)^2}{(c_h - c_{h-1})^2}\right]_+, \quad \mu_{hR}^y(y) = \left[1 - \frac{(y - c_{h+1}^{\max})^2}{(c_{h+1}^{\max} - c_h)^2}\right]_+, \tag{7}$$

(where the indices h_L, h_R indicate the left and right branches of the bell-shaped membership function $\mu_h^y(y)$), $\mu_{h,L}^y(y) = \left[1 - \frac{(y - c_h^{\max})^2}{(c_h^{\max} - c_{h-1})^2}\right]_+$.

If a new predicted signal value $y^{**}_{\max} > y^*_{\max}$ appears, then, similarly, the following membership function $\mu_{h+2}^y(y)$ is formed, while the function $\mu_{h+1}^y(y)$ is supplemented by the right branch $\mu_{h+1,R}^y(y)$.

The emergence of new membership functions theoretically should change the structure of nonlinear synapses NS_l^y and increase the number of adjustable synaptic weights. To prevent this undesirable effect, one can simply replace the function $\mu_1^y(y)$ with center $c_1 = y_{\min}$ in each synapse with the function $\mu_{h+1}^y(y)$ centered at $y^*_{\max}$ and continue the process of system forecasting-tuning, where evolution occurs only at the level of nonlinear synapses.

In the case where the analyzed sequence exhibits a decreasing trend, the system's evolution proceeds similarly.

Suppose that an input signal value $y^*_{\min} < c_1$ is received. In this case, a membership function $\mu_{h+1}^y(y)$ is formed with the center $c_{h+1}^{\min} = y^*_{\min}$, as shown in Figure 5.

The membership function $\mu_1^y(y)$ acquires an asymmetric form such that $\mu_{1R}^y(y) = \left[1 - \frac{(y - c_1)^2}{(c_2 - c_1)^2}\right]_+$, $\mu_{1L}^y(y) = \left[1 - \frac{(y - c_{h+1}^{\min})^2}{(c_{h+1}^{\min} - c_1)^2}\right]_+$, after which a new function is formed

$\mu_{1,R}^{y}(y)=\left[1-\frac{(y-c_1^{\min})^2}{(c_1^{\min}-c_2)^2}\right]_+$, which replaces the membership function in each nonlinear synapse $\mu_h^y(y)$.

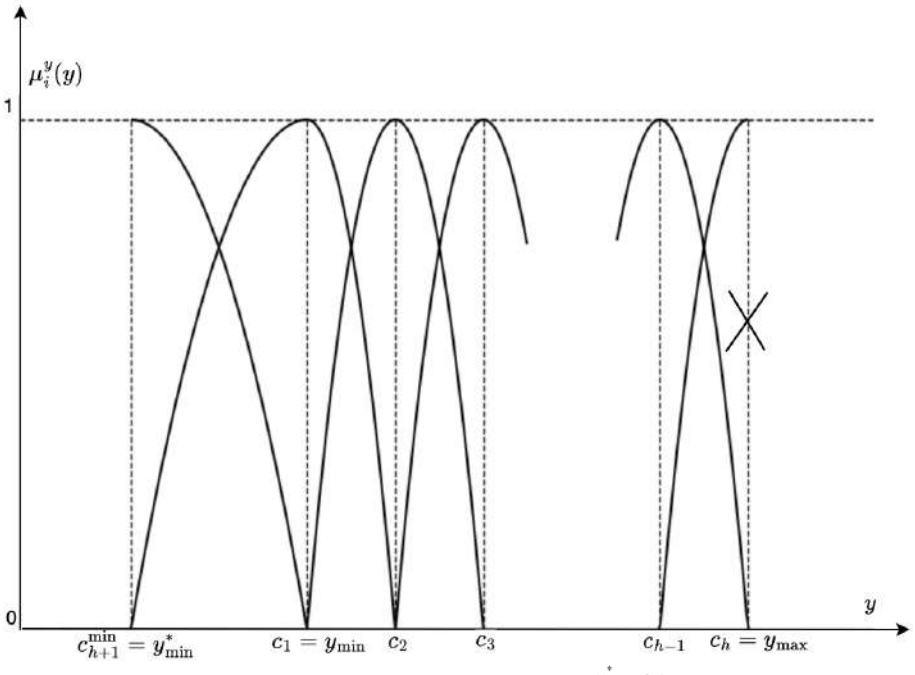


Figure 5: Evolution of the membership function system when $y_{\min}^* < c_1$

Thus, during the forecasting process of significantly non-stationary sequences, the membership function system of the current nonlinear synapse is continuously adjusted. In cases where the exogenous variable $x(k)$ is also non-stationary, the system of nonlinear synapses NS_l^x can be similarly adjusted.

Once the membership function system has been formed, it is possible to proceed with adjusting the synaptic weights of the system. Suppose that by the k-th moment in time, the prehistory vector of the analyzed sequence and the values of its membership functions are formed as follows (8):

$$\varphi(k)=(\mu_1^y(y(k-1)),\mu_2^y(y(k-1)),...,\mu_h^y(y(k-1)),\mu_1^x(x(k-1)),...,\mu_h^x(x(k-1)),...,$$
$$\mu_1^y(y(k-l)),...,\mu_h^y(y(k-l)),...,\mu_h^x(x(k-l)),...,\mu_1^y(y(k-n)),...,\mu_h^x(x(k-n)))^T. \quad (8)$$

This vector has a dimension of $2hn\times 1$ and contains $4n$ nonzero elements (corresponding to the number of activated membership functions). Next, using equation (9), the vector of synaptic weights is computed, which has the same dimension.

$$w(k-1)=(w_{11}^y(k-1),...,w_{h1}^y(k-1),w_{11}^x(k-1),...,w_{h1}^x(k-1),...,$$
$$w_{1l}^y(k-1),...,w_{hl}^x(k-1),...,w_{1n}^y(k-1),...,w_{hn}^x(k-1))^T \quad (9)$$

Then, the forecast of the sequence at moment k can be written as follows (10):

$$\hat{y}(k)=w^T(k-1)\varphi(k). \quad (10)$$

After the actual value $y(k)$ is received by the system, the synaptic weight vector can be refined using an adaptive learning algorithm [3]:

$$\begin{cases} w(k)=w(k-1)+r^{-1}(k)(y(k)-w^T(k-1)\varphi(k))\varphi(k), \\ r(k)=\alpha r(k-1)+\|\varphi(k)\|^2,\ 0\le\alpha\le 1, \end{cases} \quad (11)$$

where α is the smoothing parameter.

The newly constructed forecast is then given by $\hat{y}(k+1)=w^T(k)\varphi(k+1)$.

It is easy to see that when $\alpha=0$, equation (11) takes the form of the Kaczmarz-Widrow-Hoff gradient algorithm, which is optimally fast and best suited for working with non-stationary objects:

$$w(k) = w(k-1) + \frac{y(k) - w^T(k-1)\varphi(k)}{\|\varphi(k)\|^2}\varphi(k) = w(k-1) + (y(k) - w^T(k-1)\varphi(k))\varphi^{T+}(k) \quad (12)$$

.

Here, the symbol $(\cdot)^+$ denotes pseudoinversion.

For $\alpha = 1$, we arrive at the Goodwin-Remediuk-Kaines stochastic approximation procedure, designed for working with noise-contaminated signals. The trade-off between speed and noise robustness is ensured by varying the parameter $0 \le \alpha \le 1$.

4. Computational experiment

To perform experimental verification and compare the obtained results, we constructed an Evolving Neo-Fuzzy System with triangular membership functions and Epanechnikov functions.

As test data, synthetic time series generated using the following function (13) were used:

$$y(t) = \sin(t) + \sigma\xi(t), \quad t \in [0; 4\pi n], \quad (13)$$

where $y(t)$ represents the function values at time t, $\sin(t)$ is the primary sinusoidal signal, and σ is the noise level, determining the intensity of Gaussian noise in the data. Here, $\xi(t) \sim N(0,1)$ is a random variable normally distributed with a mean of 0 and a variance of 1. Three time series variations were considered: a clean sinusoidal signal without noise, a signal with low noise $\sigma = 0.05$, and a signal with higher noise $\sigma = 0.1$. The main criterion for evaluating forecast accuracy was the mean relative error (MRE), which allows for assessing the accuracy of predictions for each method.

Initially, forecasting was performed using two kernel membership functions defined over the initial range of time series values ($y_{\min} = -1.5;\ y_{\max} = 1.5$). The forecasting results are presented in Figures 6-8.

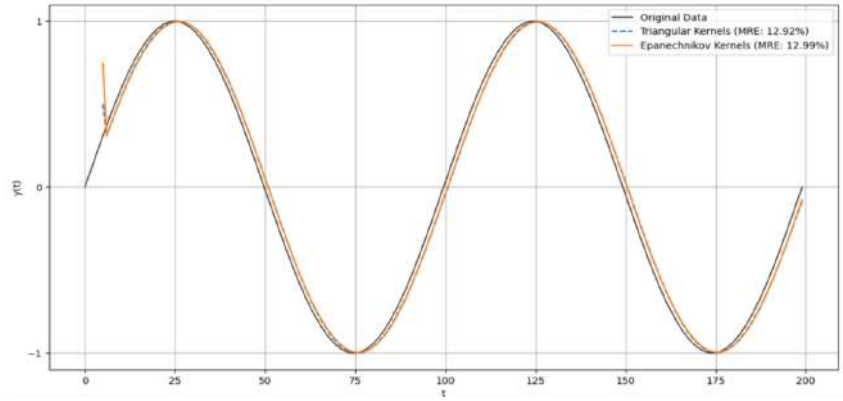


Figure 6: Forecasting results of the time series for $\sigma = 0$ without kernel evolution

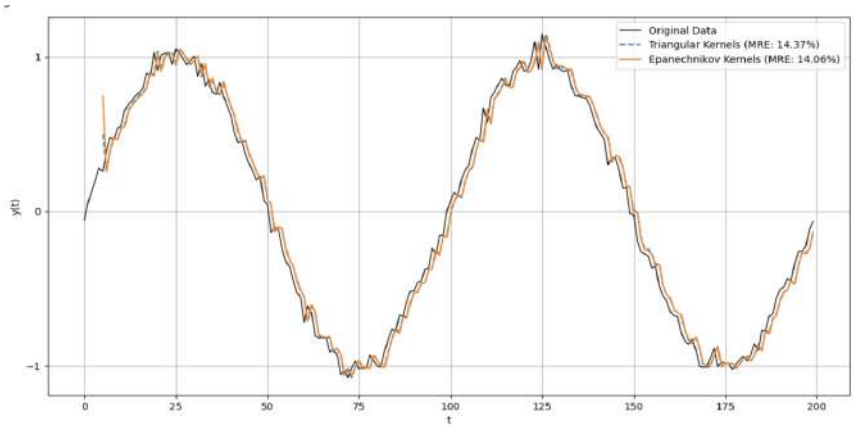


Figure 7: Forecasting results of the time series for $\sigma = 0.05$ without kernel evolution

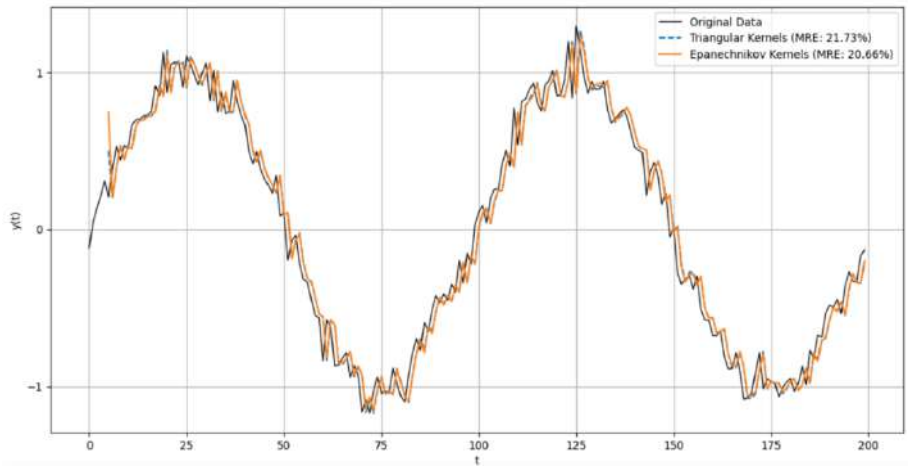
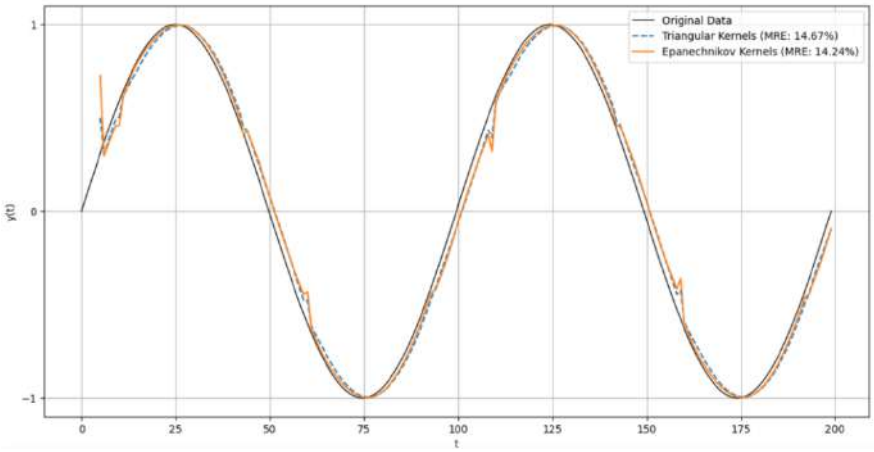


Figure 8: Forecasting results of the time series for $\sigma = 0.1$ without kernel evolution

As seen in Figures 6-8, both methods demonstrated high accuracy for a pure sinusoidal signal. However, in the presence of noise, the functions proved to be less resistant to fluctuations, leading to an increase in error. The model utilizing Epanechnikov kernels exhibited slightly better smoothing capability at low noise levels, reducing errors compared to triangular functions.

At the next stage, to verify the evolutionary component of the method, the initial interval was reduced ($y_{\min} = -0.5;\ y_{\max} = 0.5$), allowing for the simulation of the case where the observed values exceed the predefined range. The forecasting results for this case are presented in Figures 9-11.



$\sigma = 0$

Figure 9: Forecasting results of the time series for with kernel evolution

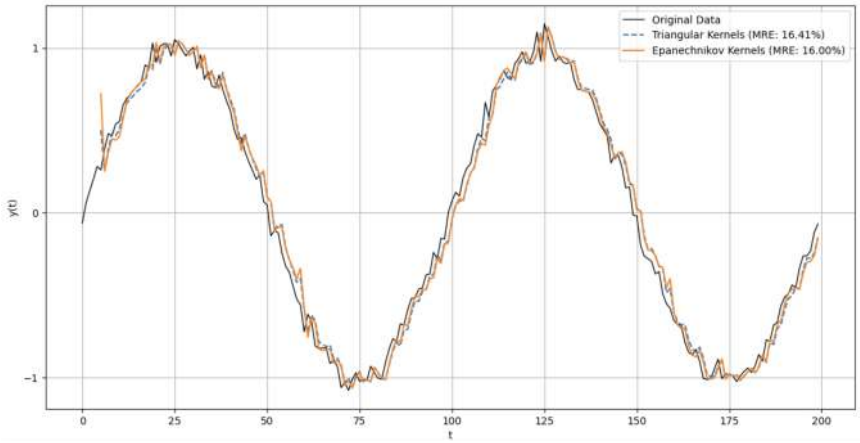


Figure 10: Forecasting results of the time series for $\sigma = 0.05$ with kernel evolution

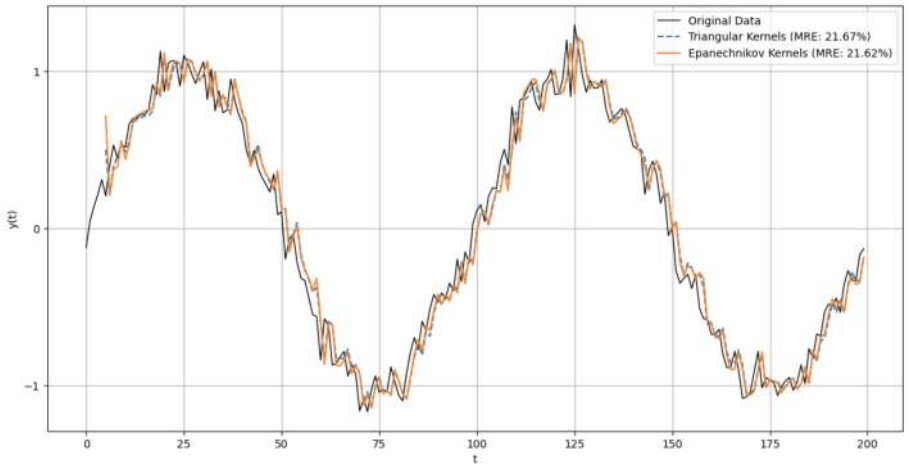


Figure 11: Forecasting results of the time series for $\sigma = 0.1$ with kernel evolution

As seen in Figures 9-11, when the initial range of the predicted variable was narrowed, the forecasting accuracy deteriorated compared to the previous numerical experiment. However, the model utilizing Epanechnikov kernels proved to be more effective.

5. Conclusion

The proposed evolutionary neo-fuzzy system is designed for forecasting significantly non-stationary stochastic and chaotic sequences perturbed by noise in an online mode, where data is processed sequentially in real-time. A key feature of the proposed system is that, during the learning process, not only synaptic weights are adjusted, but also the membership functions, which are represented by Epanechnikov kernels. Moreover, the system can be easily reconfigured in cases where the predicted sequence changes its structure.

The conducted experimental verification has demonstrated the effectiveness of the developed system. Thus, it can be concluded that the proposed approach is characterized by computational simplicity and high processing speed under conditions of non-stationarity and structural uncertainty.

Declaration on Generative AI

1. **Tools and services**: GenAI tools were not used in preparation or editing of this work.
2. **Tools' contributions:** GenAI tools were not used in preparation or editing of this work.

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Gradient-Penalty GAN Framework for High-Fidelity Fingerprint Synthesis

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Abstract

The rapid advancements in generative adversarial networks (GANs) have significantly impacted digital content synthesis, presenting both opportunities and challenges in multimedia forensics and cybersecurity. We present an Enhanced Adaptive DCGAN (EADC-GAN) for generating high-fidelity synthetic fingerprints, addressing core challenges in training stability and sample diversity. By combining Wasserstein loss with gradient penalty (WGAN-GP), instance normalization in the discriminator, and tailored architectural refinements, our model achieves strong image realism at reduced training cost. Compared to prior DCGAN-based methods, EADC-GAN synthesizes more diverse, artifact-free samples in fewer epochs, making it suitable for scalable biometric data generation. This has key implications for secure authentication, privacy-preserving biometric datasets, and adversarial robustness in cybersecurity contexts.

Keywords

Synthetic fingerprints, generative adversarial networks, WGAN-GP, DCGAN, instance normalization, biometric security, adversarial robustness, deep learning, cybersecurity, fingerprint synthesis

1. Introduction

In the modern era, artificial intelligence (AI) and information technology (IT) have become deeply embedded in nearly every aspect of human activity, driving advancements in automation, decision-making, and security. From smart homes to autonomous systems, AI-powered solutions enhance efficiency and enable novel applications across industries. In particular, AI has revolutionized forensic investigations and secure access control systems, where accurate and reliable identification methods are crucial [7, 30, 32].

Fingerprint-based biometric systems have become a cornerstone of modern security infrastructures, owing to their robustness and uniqueness in identifying individuals. With applications ranging from smartphone authentication to large-scale national identity programs, the demand for high-quality, reliable fingerprint data has soared.

However, the collection of large-scale, diverse, and privacy-preserving fingerprint datasets can be both resource-intensive and ethically fraught. This challenge has prompted research into synthetic fingerprint generation methods that can provide abundant, high-fidelity data without exposing sensitive personal information [1, 2].

Generative Adversarial Networks (GANs) have emerged as efficient tools for synthetic and realistic data generation, offering compelling results in various domains including image, video, and audio synthesis. Despite their success, early GAN models often suffered from training instabilities and mode collapse, limiting their applicability to more sensitive tasks such as fingerprint synthesis [3]. Variations like Deep Convolutional GANs (DCGANs) introduced architectures tailored for image generation, yet challenges remained, particularly when targeting both high quality and diversity in the generated outputs [4].

One promising improvement to the GAN framework is the use of gradient penalty techniques, such as those found in Wasserstein GANs with Gradient Penalty (WGAN-GP), which offer enhanced training stability. Additionally, normalization layers have a profound impact on the training dynamics and generation quality of GANs. Adaptive instance normalization (AIN), for example, has shown the capability to improve style consistency and reduce artifacts in image synthesis tasks [5, 6].

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Early approaches to fingerprint image synthesis explored traditional models such as DCGAN. In our previous work, Adaptive Deep Convolutional GAN for Fingerprint Sample Synthesis (ADCGAN), we demonstrated that a well-tuned DCGAN could generate visually convincing fingerprints [7]. However, the method exhibited two main drawbacks. First, achieving photorealistic fingerprints demanded a large number of epochs — often exceeding 1,000 — to reach acceptable quality. Second, despite eventually producing samples with realistic ridge patterns, the model became prone to mode collapse at higher epoch counts. This collapse led to repetitive samples and diminished the overall diversity of the generated dataset. The need for extensive training time also poses challenges for projects with limited computational resources or time-sensitive development cycles [7].

In this paper, we present a Gradient-Penalty GAN Framework for high-fidelity fingerprint synthesis, leveraging insights from both WGAN-GP and enhanced normalization strategies [8, 9, 10]. We build upon the insights gained from ADCGAN, refining the architecture and training strategy to yield higher-quality samples in fewer epochs while minimizing mode collapse.

By optimizing the instance normalization layers and incorporating gradient penalty, we aim to address training instability and mode diversity issues that often hinder fingerprint GAN models. Our experimental evaluations demonstrate that this architecture not only produces more realistic and varied fingerprint images but also reduces the computational overhead commonly associated with GAN enhancements.

Crucially, the synthesized fingerprints can bolster biometric research by providing large-scale datasets and facilitating the development of advanced, secure authentication systems without compromising user privacy.

Despite advances in GAN-based fingerprint synthesis, existing models often struggle with training instability, mode collapse, and insufficient diversity in generated samples. Additionally, many methods require extensive computational resources and training time, limiting their practical use in scalable biometric systems. This work addresses these limitations by proposing a more stable, efficient GAN framework capable of producing realistic, high-resolution fingerprint images with minimal redundancy.

2. Related Work

2.1. GAN-Based Image Synthesis Approaches

GANs have become a central method for synthesizing diverse image datasets, including biometric images such as fingerprints. Early efforts often relied on the DCGAN framework, which demonstrated that transposed convolution layers could capture essential fingerprint patterns. However, these classical DCGANs typically require extensive training, and they remain susceptible to mode collapse — where the generator converges to limited variations of the same fingerprint. Recent approaches have aimed to mitigate these issues by integrating more advanced loss functions and architectural refinements, making GAN-based finger-print synthesis both more efficient and more robust in capturing fine ridge details [5, 6].

2.2. Fingerprint Synthesis Techniques

Early fingerprint generation efforts often employed parametric and procedural models, focusing on ridge flow simulation and minutiae placement through mathematical functions. Techniques such as Gabor-based filters, Fourier transforms, and partial differential equations (PDEs) aimed to replicate key fingerprint structures without relying on large training sets. Although these methods can yield convincing ridge patterns and minutiae distributions, they sometimes lack the capacity to produce the extensive variability needed for modern biometric applications.

In contrast, deep learning–driven approaches like GANs learn distributional properties directly from real data, offering greater flexibility and diversity in synthesized outputs. Beyond standard DCGAN-based solutions, advanced architectures — such as StyleGAN and CycleGAN — further refine texture details, enhance global coherence, and address common pitfalls like mode collapse. Together, both classical (model-based) and deep learning–based techniques enrich the toolbox for generating comprehensive, privacy-friendly fingerprint datasets [7, 11, 12].

2.3. Normalization in GANs

Normalization layers are crucial for stabilizing GAN training, and adaptive instance normalization offers particular benefits for image synthesis tasks that depend on local texture fidelity. While batch normalization averages statistics across a mini-batch, instance normalization normalizes each sample independently, helping preserve distinctive ridges and fine details in synthetic fingerprints. Instance normalization can reduce style variations within a single batch — an advantage when the primary goal is to maintain consistent textural cues. As a result, integrating instance normalization, especially in the discriminator, can sharpen feature detection and further mitigate common GAN pitfalls such as training instability and overly uniform outputs [13, 14].

2.4. Gradient Penalty Methods (WGAN-GP and Beyond)

The Wasserstein GAN (WGAN) framework addresses two key shortcomings in conventional GANs: vanishing gradients and unstable training. By replacing the standard generator-discriminator loss with the Wasserstein distance, WGAN provides a meaningful gradient signal that promotes better convergence. To further stabilize training, WGAN with Gradient Penalty (WGAN-GP) incorporates a gradient penalty term that enforces Lipschitz continuity without resorting to weight clipping. This penalty term substantially reduces mode collapse and improves sample diversity. In the context of fingerprint synthesis, WGAN-GP's training stability helps produce more varied and realistic fingerprint ridges over fewer epochs [8, 9].

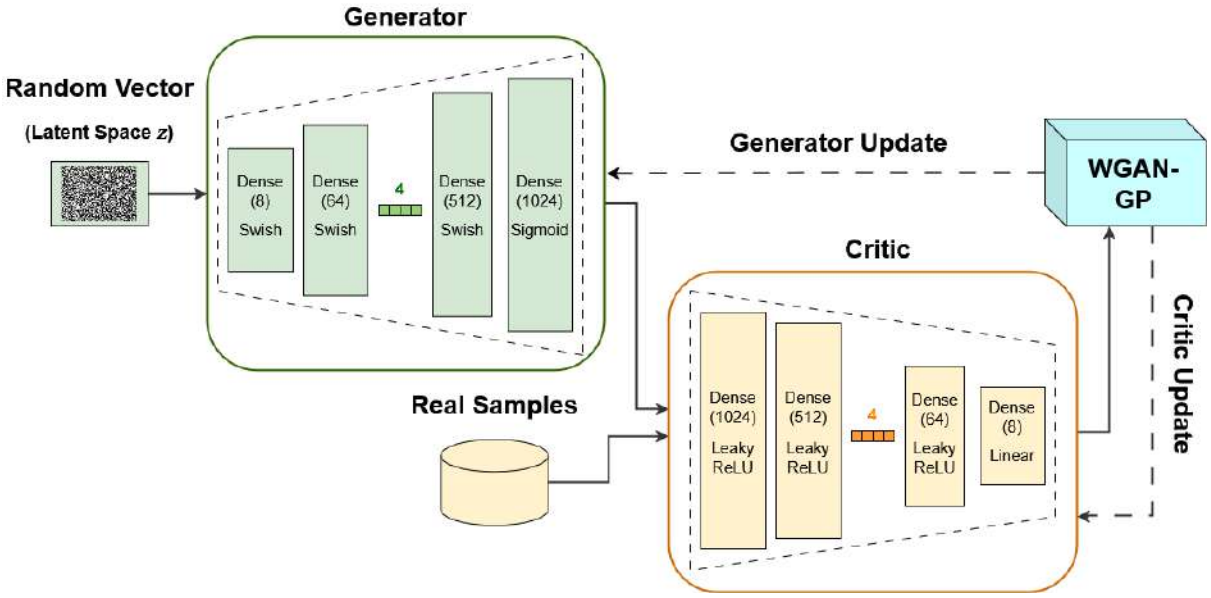

Figure 1: Flowchart illustrating the workflow of the WGAN-GP architecture

Unlike classical DCGAN-based approaches that rely heavily on batch normalization and often exhibit mode collapse, our method introduces instance normalization in the discriminator and leverages WGAN-GP for improved gradient flow. This combination enhances both training stability and output diversity. While models like StyleGAN and CycleGAN achieve high visual fidelity, they often require complex tuning and are not specifically tailored to biometric features [5, 15, 17]. In contrast, our architecture is optimized for fingerprint synthesis, balancing computational efficiency with domain-specific texture preservation.

3. Proposed Methodology

3.1. Normalized DCGAN Architecture

The proposed model builds upon the standard DCGAN framework — originally designed to generate high-quality images through transposed convolutions in the generator and strided convolutions in the discriminator.

However, instead of using batch normalization throughout, we use instance normalization in the discriminator to improve training stability and capture finer textures critical for biometric features.

DCGAN was chosen as the foundation due to its proven effectiveness in structured image generation, including biometric textures. Its simplicity and modularity make it highly adaptable for fingerprint synthesis. By replacing batch normalization with instance normalization and integrating WGAN-GP, we retain DCGAN's strengths while resolving its typical weaknesses — namely, training instability and low sample diversity. This adapted framework strikes a practical balance between architectural simplicity, computational efficiency, and output quality.

Generator follows a classic DCGAN-like upsampling pipeline, which transforms a latent noise vector into a full-resolution fingerprint image through stacked transposed convolutional layers, batch normalization, and ReLU activations.

Discriminator mirrors the generator's structure in a downsampling fashion but replaces batch normalization with instance normalization layers. LeakyReLU activations are retained to preserve gradient flow. Instead of normalizing over the entire batch, instance normalization (IN) scales and shifts each sample independently. Fingerprint images demand precise ridge patterns. IN helps retain such fine-grained textures without inadvertently averaging them out across a mini-batch [13, 15, 16, 17].

By combining instance normalization with the WGAN-GP training strategy, the model is less prone to collapsing to repetitive samples. Empirical observations show that instance normalization can better capture local variations, which are paramount for realistic fingerprint synthesis. In the following sections, we detail how gradient penalty is integrated to further stabilize training and discuss the specific loss functions and optimization protocol that tie into the model architecture.

Table 1
Model Configuration

Layer Type	Configurations
Fully Connected (Generator)	#units: 512×8×8
Reshape & BatchNorm	#features: 512, BN, ReLU
Transposed Convolution	#filters: 256, k: 4×4, s: 2, p: 1
BatchNormalization + ReLU	#features: 256, BN, ReLU
Transposed Convolution	#filters: 128, k: 4×4, s: 2, p: 1
BatchNormalization + ReLU	#features: 128, BN, ReLU
Transposed Convolution	#filters: 64, k: 4×4, s: 2, p: 1
BatchNormalization + ReLU	#features: 64, BN, ReLU
Transposed Convolution (Output)	#filters: 1, k: 4×4, s: 2, p: 1, activation: Tanh
Input (Discriminator)	1×128×128 grayscale images
Convolution	#filters: 64, k: 4×4, s: 2, p: 1, activation: LeakyReLU(0.2)
Convolution + InstanceNorm	#filters: 128, k: 4×4, s: 2, p: 1, activation: LeakyReLU(0.2)
Convolution + InstanceNorm	#filters: 256, k: 4×4, s: 2, p: 1, activation: LeakyReLU(0.2)
Convolution + InstanceNorm	#filters: 512, k: 4×4, s: 2, p: 1, activation: LeakyReLU(0.2)
Convolution (Output)	#filters: 1, k: 4×4, s: 1, p: 0, activation: Linear

3.2. Integration of Gradient Penalty

To stabilize training and mitigate mode collapse, we adopt the WGAN-GP framework, which enforces Lipschitz continuity through a gradient penalty on the discriminator's output. Unlike weight clipping used in early WGANs, this penalty regularizes gradient norms for interpolated real and fake samples, improving convergence without harming model capacity [8, 9].

In each training iteration, the algorithm samples a random scalar α from a uniform distribution $U(0,1)$. A point $\hat{x}$ is then created by interpolating between a real sample x_{real} and a generated sample x_{fake}. The discriminator's gradient is computed on $\hat{x}$.

Let's formulate the loss. If D denotes the discriminator, its Wasserstein distance–based objective incorporates an added penalty term:

$$\lambda_{gp} \cdot (\| \nabla D(\hat{x})\|_2 - 1)^2 \tag{1}$$

where λ_{gp} is a hyperparameter dictating the penalty's strength.

By penalizing large deviations of $\| \nabla D(\hat{x})\|_2$ from 1, the discriminator remains closer to a valid 1-Lipschitz function, leading to more reliable gradients for the generator [8, 9].

The gradient penalty term mitigates abrupt updates in the discriminator that commonly cause training to diverge. By preserving a stable gradient flow, the generator avoids collapsing to a narrow subset of fingerprints. Because the discriminator's updates remain well-conditioned, the model can converge to realistic fingerprint patterns in fewer epochs compared to weight-clipped or standard DCGAN setups [8, 9].

In the next sections, we detail how this WGAN-GP loss formulation is combined with instance normalization, specialized generator and discriminator architectures, and the overall training workflow to produce high-quality, diverse fingerprint images.

3.3. Loss Functions and Optimization Strategy

The training process adopts the WGAN-GP framework, which replaces the traditional adversarial loss with an objective based on the Wasserstein distance. Below are the key components [8, 9].

Discriminator (Critic) Loss:

$$L_D = E_{x \sim p_{data}}[D(x)] - E_{z \sim p_z}[D(G(z))] + \lambda_{gp} E_{\hat{x}}\left[(\| \nabla D(\hat{x})\|_2 - 1)^2\right] \tag{2}$$

where L_D is the discriminator loss, E is expectation, D is the discriminator, G is the generator, x are real samples, z are noise vectors from a prior distribution (e.g., $N(0,1)$), $\hat{x}$ is an interpolated sample between real and generated data, and λ_{gp} scales the gradient penalty.

Generator Loss:

$$L_G = -E_{z \sim p_z}[D(G(z))] \tag{3}$$

where L_G is the generator loss.

Adam is employed for both generator and discriminator, with learning rate $\approx 2 \times 10^{-4}$, $\beta_1 = 0.5$, and $\beta_2 = 0.999$. These parameters promote stable convergence in convolutional architectures, particularly with the gradient penalty term.

A common strategy in WGAN-based setups is to update the discriminator more often than the generator (e.g., 5:1 ratio), ensuring the critic remains sufficiently accurate to guide generator updates.

Gradient penalty enforces a smooth, 1-Lipschitz constraint without resorting to weight clipping. Instance normalization in the discriminator helps preserve detailed ridge features in fingerprints and ensures stable gradient flow [8, 9].

By combining WGAN-GP loss functions, careful hyperparameter tuning, and selective update frequencies, the model converges faster and produces higher-fidelity fingerprint images than standard DCGAN-based methods.

3.4. Algorithmic Workflow

The training pipeline, informed by the enhanced EADC-GAN implementation, proceeds through a structured sequence of steps designed to systematically refine both the generator and discriminator networks. Initially, the model configurations and hyperparameters are defined, including the number of epochs, batch size, latent dimension, learning rate, and the gradient penalty coefficient. Fingerprint images, resized to 128×128 pixels and normalized to the [−1,1], are loaded through a shuffling mechanism that ensures an unbiased sampling process across mini-batches.

Once the data is loaded, the generator and discriminator networks are initialized. The generator uses DCGAN-like architecture to transform a latent vector $z \in R^{100}$ into a 128×128 image. It applies transposed convolutions, batch normalization, ReLU activations, and ends with a Tanh layer. The discriminator mirrors a downsampling approach, incorporating instance normalization and LeakyReLU activations. To enable stable convergence, both networks initialize their learnable parameters with random values drawn from a normal distribution centered at zero with a standard deviation of 0.02.

The core training cycle repeats for each epoch and processes one mini-batch of fingerprint data at a time. In each iteration, the discriminator is first updated by sampling real fingerprint images x_{real} from the dataset and generating fake images $x_{fake} = G(z)$ from randomly sampled noise vectors z. The Wasserstein distance is then computed as the difference in discriminator outputs on real and fake samples, and the gradient penalty term is imposed through an interpolation strategy that regularizes the norm of the discriminator's gradients. These gradient-based objectives are combined, and the discriminator parameters are updated accordingly via backpropagation with an Adam optimizer, using momentum parameters $\beta = (0.5, 0.999)$.

After the discriminator update, the generator is refined at a reduced frequency (for instance, every five discriminator iterations) to maintain a reliable critic. In this phase, fresh noise vectors are drawn from the latent distribution, passed through the generator, and evaluated by the discriminator. The generator's loss function aims to maximize the discriminator's output on these synthesized images, effectively minimizing the negative Wasserstein distance. By backpropagating this signal, the generator weights are adjusted to create more plausible and diverse fingerprint images in subsequent iterations.

Throughout training, the system periodically saves both model checkpoints and synthetic images generated from a fixed set of noise vectors. These outputs allow for consistent evaluation of the generator's progression over time and facilitate direct comparison across epochs. Upon completion, the final weights of the generator and discriminator are stored for downstream usage, such as bulk synthetic fingerprint generation or further fine-tuning. By blending frequent discriminator updates, a gradient penalty mechanism, and controlled generator refinement, the workflow produces high-fidelity and structurally diverse fingerprint images within a stable and computationally efficient training regime.

Below is a comparison table that presents architectural differences between the models — our previous ADC-GAN and EADC-GAN [7].

3.1. Theoretical Contribution and Novelty

This work presents a novel synthesis of two stabilizing strategies — gradient penalty from WGAN-GP and instance normalization in the discriminator — to improve the fidelity and diversity of fingerprint generation. While both techniques have been explored separately in GAN literature, their combined use and fine-tuning in a domain-specific architecture for fingerprint synthesis is new, and, to our knowledge, no prior fingerprint-synthesis study combines IN and WGAN-GP. Our results demonstrate that this hybrid strategy enables faster convergence, reduces mode collapse, and preserves fine-grained biometric details more effectively than conventional batch-normalized DCGANs or standard WGAN-GP models.

Table 2
Comparison Table of ADC-GAN and EADC-GAN

Feature	ADC-GAN	EADC-GAN
Image Size	64 × 64 pixels (images are resized and center-cropped to 64×64).	128 × 128 pixels (images are resized to 128×128).
Latent Dimension	100 (input noise vector size is 100).	100 (input noise vector size is 100).
Training Epochs	1200 epochs.	200 epochs.
Loss Function	GAN loss and Binary Cross-Entropy (BCE) loss for both generator and discriminator.	Wasserstein GAN loss with gradient penalty (WGAN-GP): the discriminator loss is computed as the negative difference between real and fake outputs plus a gradient penalty term ($\lambda = 10$).
Normalization (G)	Batch normalization is used after each deconvolution (ConvTranspose2d) layer except the output layer.	Batch normalization is applied in the generator after the fully connected layer and during deconvolution.
Normalization (D)	Batch normalization is applied (after the first Conv2d layer).	Instance normalization is used instead of batch normalization in most layers, which may help stabilize training when combined with gradient penalty.
Optimizer & Learning Rate	Adam optimizer with separate learning rates: Generator lr = 0.0001, Discriminator lr = 0.0002; $\beta_1 = 0.5$, $\beta_2 = 0.999$.	Adam optimizer for both networks with a common learning rate of 0.0002; $\beta_1 = 0.5$, $\beta_2 = 0.999$.
Generator Architecture	A sequential model that uses a series of ConvTranspose2d layers to upsample the latent vector directly into a 64×64 image; final activation is Tanh.	Starts with a fully connected (fc) layer that projects the latent vector into a feature map (reshaped to an 8×8 spatial size) followed by several ConvTranspose2d layers to upscale to 128×128; final activation is Tanh.
Discriminator Architecture	A sequential network of Conv2d layers with BatchNorm (except the first layer) and LeakyReLU activations; ends with a Sigmoid to output a probability score.	A sequential network of Conv2d layers using instance normalization and LeakyReLU activations; does not use a Sigmoid activation in the final layer – it outputs a single scalar value for WGAN-based loss calculation.
Unique Features	Implements a modified DCGAN architecture with BCE loss, adaptive learning rates, robust weight initialization, and batch normalization techniques.	Incorporates instance normalization in the discriminator, modified batch normalization, and a gradient penalty term in the loss (WGAN-GP), improving training stability, computational effectiveness, and image quality in higher resolution settings.

Furthermore, we extend the practical utility of WGAN-GP by applying it to a biometric domain with strict texture preservation needs, showing its scalability to higher resolutions (128×128) with reduced training costs. This framework can serve as a foundational baseline for synthetic biometric data generation, adversarial robustness studies, and privacy-focused authentication system design.

4. Experimental Setup

4.1. Datasets and Preprocessing

The experimental analysis utilizes a curated subset of fingerprint images drawn from a publicly available biometric dataset — SOCOFing [18]. The data includes grayscale samples, exhibit variability in ridge patterns, and contrast.

To achieve consistency across samples, each fingerprint image is resized to a fixed spatial dimension of 128×128 pixels and normalized to the range [−1,1]. This normalization aligns with the output of the generator's Tanh activation, facilitating stable training dynamics and seamless comparisons across different batches.

The grayscale format (single-channel) not only reduces computational overhead but also highlights finer ridge and valley structures, which are central to realistic fingerprint generation. Throughout the preprocessing pipeline, data is split into training and validation subsets, although the adversarial framework primarily relies on the training partition for iterative updates.

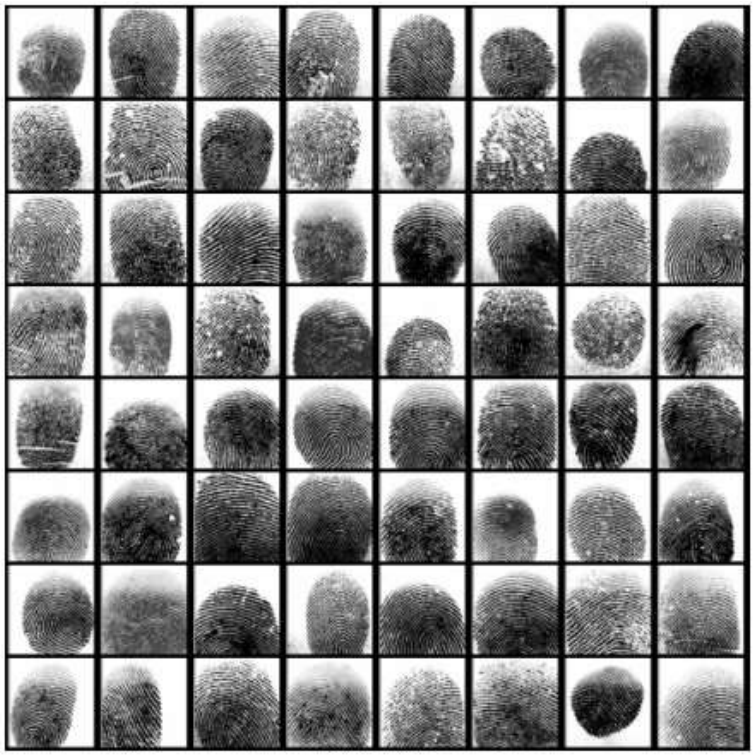

Figure 2: SOCOFing real data — fingerprint scans

4.2. Evaluation Metrics

The model monitors training progress primarily through discriminator and generator loss values, as well as periodic visual inspection of generated samples. By regularly printing the Wasserstein-based objective for both networks, we were able to quickly identify training instabilities. Meanwhile, saving a fixed batch of synthetic fingerprint images over multiple epochs provides a direct, qualitative perspective on improvements in ridge fidelity and overall realism.

Relying on losses and sample outputs offers a lightweight yet effective evaluation strategy. In high-detail domains like fingerprint synthesis, real-time visual checks can be more intuitive than abstract numeric scores, enabling domain experts to spot subtle artifacts or textural inconsistencies. This

approach also simplifies model development by reducing the computational overhead of advanced metrics (e.g., Fréchet Inception Distance), which often require large external classifiers or additional memory usage.

If a more robust, quantitative benchmark is desired, metrics like FID or Inception Score can be incorporated at a later stage to complement the qualitative insights gained from losses and sample images.

4.3. Implementation Details and Hyperparameter Settings

Model training is conducted using PyTorch, leveraging GPU acceleration. Both generator and discriminator networks are initialized with weights drawn from a normal distribution ($\mu=0$, $\sigma=0.02$), consistent with DCGAN best practices. The Adam optimizer [19] is applied to each network's parameters.

The discriminator (equipped with instance normalization) is updated for every mini-batch, while the generator receives updates at a slightly reduced frequency (e.g., once every five discriminator steps), preserving a balanced training signal.

The gradient penalty coefficient λ_{gp} is set to 10, based on prior WGAN-GP literature that suggests it effectively constrains the gradient norm [8, 9].

Training proceeds for up to 200 epochs — substantially fewer than the 1,000+ epochs sometimes required by earlier DCGAN-based methods — owing to the stabilizing influence of gradient penalty and the enhanced texture preservation afforded by instance normalization.

5. Results and Analysis

5.1. Qualitative Assessment

Generated fingerprint samples display high-fidelity ridge patterns and minimal visual artifacts, particularly in mid-to-late training epochs. Qualitatively, synthetic images exhibit distinct papillary lines, consistent contrast levels, and plausible global orientations that resemble real biometric data. By periodically saving and reviewing the generator's outputs, we could observe a steady progression from coarse, noisy impressions to well-defined ridge structures.

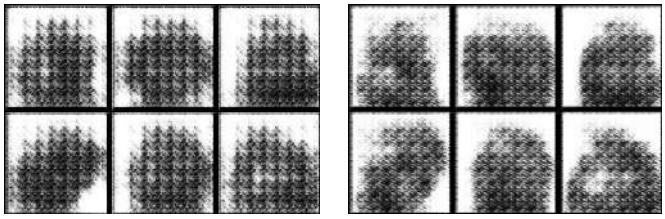

Figure 3: Synthesized samples — results after 10 epochs (left) and 20 epochs (right) of EADC-GAN model training

Notably, improvements occur with only 170—200 epochs compared to 1200 epochs of the earlier DCGAN-based model, reflecting the stabilizing influence of the gradient penalty and instance normalization.

5.2. Normalization and Penalty Variants

Ablation experiments indicate that substituting batch normalization with instance normalization in the discriminator enhances texture preservation and mitigates mode collapse. When batch normalization is reintroduced, training exhibits higher variance in discriminator loss and a slight decline in sample diversity. Similarly, reducing or removing the gradient penalty coefficient (λ_{gp}) increases the likelihood of training instabilities and partially reintroduces repetitive patterns in generated outputs.

These findings confirm that both instance normalization and a carefully tuned gradient penalty are key contributors to generating varied fingerprints.

5.3. Computational Efficiency and Scalability

Despite incorporating gradient penalty and additional normalization layers, the model proves computationally efficient relative to extended training regimes of-ten required by baseline DCGANs.

In practical experiments, fewer total epochs are needed to attain comparable — or superior — visual fidelity. Moreover, the approach scales well on standard GPU hardware, supporting batch sizes large enough to accelerate convergence. This efficiency stems from the stable gradient updates afforded by WGAN-GP, which reduce the need for extensive hyperparameter searches and lessen the risk of early divergence, making the framework suitable for larger datasets or more complex biometric tasks.

5.4. Evaluation of Results

The training dynamics of the model exhibit an initial phase of instability, particularly in the discriminator's loss, which starts at an excessively high value in the first epoch. This behavior suggests that the gradient penalty term may have been dominating due to scaling. However, within the first few epochs, the discriminator loss rapidly decreases and stabilizes around -0.5 to -0.8, indicating that the discriminator quickly adapts to distinguishing real from generated samples. Simultaneously, the generator loss begins at a low value and progressively increases, demonstrating an initial struggle to generate realistic samples. By epochs 10–20, the adversarial balance improves, as evidenced by the increasing generator loss and stabilized discriminator loss, suggesting that the generator is effectively learning to produce more convincing outputs.

Below are samples of artificial fingerprints generated by EADC-GAN after 170 and 200 epochs, respectively.

Figure 4: Synthesized fingerprints — results after 170 epochs (left) and 200 epochs (right) of EADC-GAN model training

For comparison, the results after 1,000 to 1,300 training epochs are presented below. The samples clearly demonstrate mode collapse, along with low-resolution quality.

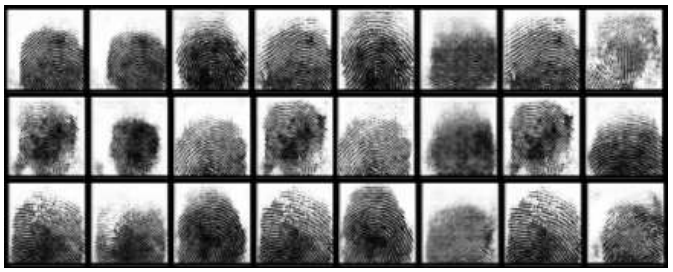

Figure 5: Generated results obtained from 1000 to 1300 training epochs

Beyond epoch 40, the training stabilizes further, with the generator loss continuing to rise and reaching values around 4.0 by epoch 100. This steady increase indicates that the generator is persistently improving its ability to generate high-quality images, while the discriminator maintains a controlled dominance. The gradient penalty (λ=10) appears to regulate training effectively, preventing extreme discriminator outputs and ensuring stable adversarial interactions. However, the increasing generator loss may warrant further investigation to rule out potential training inefficiencies or diminishing discriminator feedback. Overall, the observed loss trends suggest that the

model is learning effectively, but parameter tuning — especially for the gradient penalty coefficient — could further optimize convergence dynamics.

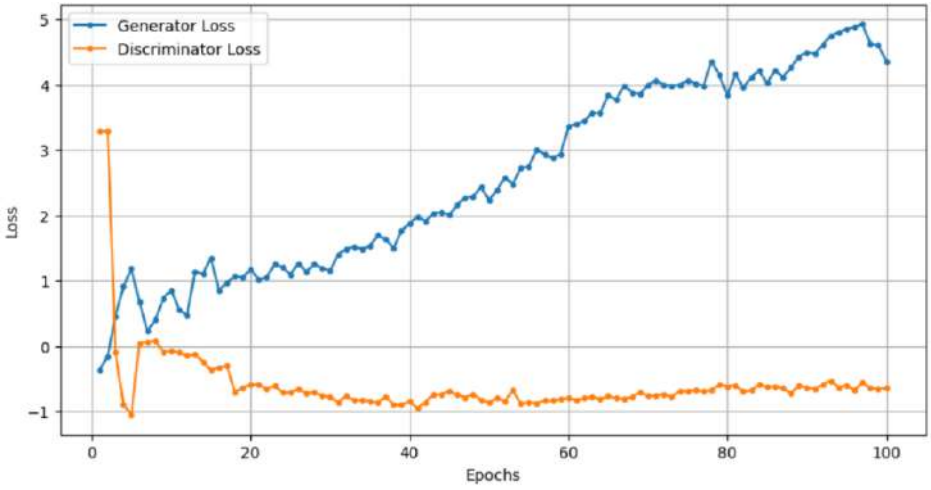

Figure 6: Generator and discriminator loss during training.

The model was trained using the Kaggle cloud environment with an NVIDIA Tesla P100-PCIE-16GB GPU, running CUDA 12.6 and driver version 560.35.03.

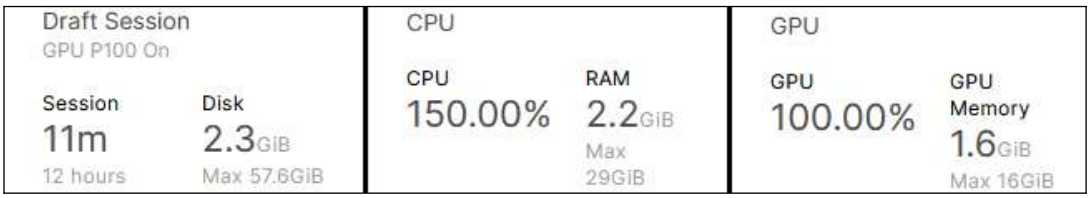

Figure 7: System resource utilization during model training on NVIDIA Tesla P100 GPU

6. Cybersecurity and Biometric Implications

6.1. Integration in Biometric Authentication Systems

The capacity to generate high-fidelity synthetic fingerprints raises important considerations for both security researchers and practitioners. On one hand, it offers a privacy-preserving means of advancing biometric systems by enabling robust testing and algorithmic development without exposing sensitive personal information. On the other hand, it introduces potential vulnerabilities that adversaries could exploit if protective measures are not effectively enforced [20, 21].

By accurately capturing the visual and structural attributes of real fingerprints, the proposed generative model can supply large synthetic datasets for training and validation in biometric authentication systems. These "privacy-friendly" samples minimize the legal and ethical constraints associated with collecting user data at scale, while still reflecting realistic ridge patterns crucial for ensuring system reliability.

In practice, developers can use this influx of synthetic samples to enhance feature extraction methods, improve fingerprint-matching algorithms, and conduct comprehensive stress testing against external conditions such as image quality variations or sensor discrepancies. The resulting improvements in accuracy and robustness can bolster consumer confidence in biometric authentication solutions across various sectors, including mobile devices, secure facility access, and e-Government initiatives [22].

6.2. Adversarial Vulnerabilities and Mitigation

While the generation of realistic fingerprint images aids legitimate research, it concurrently highlights potential avenues for adversarial attacks. Malicious actors could use convincing synthetic

fingerprints to probe or bypass fingerprint recognition systems. This possibility underscores the need to develop spoof detection or presentation attack detection mechanisms capable of distinguishing artificially generated ridges from authentic biometric inputs.

Countermeasures may include specialized classifiers trained on adversarially generated images, advanced liveness detection technologies, or multi-factor authentication procedures that combine fingerprint data with other identifiers. By integrating these preventative strategies, security experts can leverage the benefits of synthetic biometric training data without compromising user safety and privacy [23, 24, 25, 26, 27, 28, 29].

7. Conclusion and Future Directions

High-fidelity synthetic fingerprints offer both opportunities for biometric advancement and risks of misuse. They enable privacy-preserving testing and development but also raise security concerns if safeguards are lacking.

While the proposed EADC-GAN framework outperforms traditional DCGANs in terms of convergence speed and visual fidelity, it still requires substantial GPU resources for optimal performance. Moreover, the current evaluation relies primarily on qualitative assessments, lacking explicit quantitative metrics such as the Fréchet Inception Distance or specialized fingerprint matching scores. Additionally, the model's ability to generate ultra-high-resolution fingerprints (e.g., >256×256 pixels) remains to be fully explored — a critical requirement for certain forensic or high-security applications.

Future work may focus on scaling the architecture to support higher resolutions and embedding domain-specific fingerprint features tailored for forensic or advanced biometric scenarios [30–32]. Exploring alternative normalization strategies, such as hybrid or adaptive instance normalization [33-35], could further enhance ridge style consistency. Incorporating quantitative evaluation metrics specific to fingerprint quality — potentially benchmarked against live-capture datasets — would also strengthen the model's practical utility.

Finally, integrating spoof-detection modules directly into the training loop may help preemptively mitigate adversarial vulnerabilities [36-39]. By pursuing these directions, the proposed framework can evolve into a robust and versatile tool for both secure biometric authentication [40, 41] and adversarial AI research [42, 43].

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Intelligent controller of helicopter turboshaft engines' gas temperature with compensation of transient process's inertial delays and optimization

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Abstract

This research presents the development of an intelligent controller for the helicopter turboshaft engines gas temperature, aimed at compensating for the measuring sensor's inertial delays and optimizing transient processes. The aim is to compensate for inertial delays $\tau \approx 0.025$ seconds and optimize transient processes. The method is based on a double summation circuit with a channel selector, comparing signals from a thermocouple and a gas-generator rotor speed sensor, and an adaptive observer based on Pade approximation and Taylor series expansion provides a prediction of the state at $t + \tau$. The intelligent control law includes a proportional-integral-differential structure with the coefficients γ_i correction via gradient descent. To refine the delay estimate, a two-layer fully connected multilayer perceptron with a SmoothReLU activation function is implemented trained on flight test data was implemented, which reduced τ to 0.016 seconds (−36 %). This module allows to approximate nonlinear relations between input features and the delay value, which ensures the control signal's timely correction and the system's adaptation to changing operating conditions. Modeling of the system in the Matlab Simulink environment demonstrated a significant improvement in the transient process characteristics: overshoot was reduced from 8.0 to 1.5 %, and the mode establishment time was reduced from 4.2 to 3.3 seconds. The neural network module testing showed high predicting accuracy (99.537 % with losses of 0.511 %), confirmed by the determination coefficient R^2 = 0.9717. The neural network use made it possible to reduce the delay value to 0.016 seconds, which corresponds to an improvement of 36 % compared to traditional methods. The obtained results indicate a proposed technique's high potential for improving the helicopter turboshaft engines automatic control system's dynamic accuracy and stability.

Keywords

Automatic control system, gas temperature, transient process, helicopter turboshaft engine, neural network, training, accuracy

1. Introduction

The aviation industry's evolution is closely related to the helicopter's new types of operation (e.g., Eurocopter AS350, Eurocopter EC145, Eurocopter EC225 Super Puma, etc.), characterized by high speed and long range, which requires increasingly sophisticated automation control systems [1, 2]. The manual and automatic control synthesis, as well as the latter rapid development, forced designers to create not only visual devices for humans but also a sensor set, which signals directly affect the automatic system's subsequent links [3]. The most important characteristic of helicopter turboshaft engines (TE) is the gas temperature in front of the compressor turbine, since it significantly determines both the power plant efficiency and its reliability [4, 5]. Thus, these parameters maintaining accurate values is critical to ensuring the helicopter TE's stable operation.

To maintain the set parameters at a fixed throttle position or to change them according to a given law depending on flight conditions and operating modes, the helicopter TE automatic control systems (ACS) are used [6]. The main requirement for modern ACS is compensation for the temperature sensor's inertia so that the measuring devices function without delays [7, 8].

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The main requirements for helicopter TE ACS include the high static accuracy to maintain a given range (0.3…0.5%), efficiency with a quick response to control (2…3 seconds), and transient processes close to monotonous, which ensures regulation without drops (2…4%) and with a minimum stabilization time [9, 10]. These strict and contradictory conditions cannot be solved by standard methods, which creates the developing complex task of multifunctional automatic control systems for helicopter TE.

2. Related Works

There are known helicopter TE ACS [11–13] that affect a single control parameter, which is the fuel consumption in the combustion chamber, which includes measuring devices for input signals, comparison elements, and an actuator, and the signal from the gas temperature controller directly adjusts the rotor speed controller setting. This scheme's main disadvantage is the reduction in stability reserves and permissible gain factors, which worsens static and dynamic accuracy, and to eliminate this effect, systems with a selector are used, excluding controllers' joint operation area and thereby improving the system's overall characteristics [14, 15]. The helicopter TE gas temperature control system presented in [16] uses a correction link with a differentiator, multiplier blocks, and adders to compensate for the dynamic error caused by the first temperature sensor inertia. The correction coefficient at the derivative changes based on the current gas flow rate signal, which ensures high measurement and control accuracy. However, the scheme's key disadvantage is that in transient modes, the rotor speed and temperature channel's interaction through the selector is not taken into account, which reduces the inertial delay compensation efficiency.

The helicopter TEs gas temperature control using the controller presented in [17] is carried out through correcting devices for the control channels transfer functions changing. This allows for minimizing overshoot and ensuring stable engine operation in various modes. However, its key disadvantage is related to the inertial delays compensation: since the transfer functions correction depends on the velocity pressure, changes in the system occur with a delay, which can cause a temporary mismatch between the required and actual parameters, especially with sharp changes in engine operating modes.

In [18] the engine temperature controller is presented that uses a double summation scheme, in which the measured temperature signal is compared with the set value, and the correction is carried out by a nonlinear element that compensates for the delay in the compressor turbine blades heating. Due to the inertial link, the rotor speed signal is corrected, which eliminates sharp increases in gas temperature in front of the compressor turbine, thereby improving the transient processes quality. As a result, the fuel consumption changes proportionally to the summing amplifier's output signals, ensuring stable and accurate regulation of the engine operation. This controller's main limitation is the long return time to the original mode, due to the isodromic feedback inertia. The intelligent component introduction will allow dynamically optimizing the control parameters and reducing the system response time to changes in operating conditions.

The helicopter TEs intelligent gas temperature controllers integrate modern automatic control methods, including correction links with differentiators, nonlinear elements, and double summation schemes, which allow achieving high accuracy and stability of operation [19, 20]. They ensure overshoot minimization and fast system response, which is critically important for modern helicopters with high-speed and long-range characteristics. However, these systems key disadvantage is insufficient compensation for the measuring sensors inertial delays, which leads to the parameters temporary mismatch in transient modes. Some schemes, for example, [21, 22], aimed at regulating fuel consumption, experience a decrease in stability margins and permissible gain factors, which negatively affects the static and dynamic accuracy of regulation.

3. Goal and Objectives

Thus, a goal of this paper is to develop the helicopter TEs gas temperature intelligent controller, compensating for the measuring sensors inertial delays and optimizing transient processes. To achieve the goal the following objectives are formed: (i) developing the intelligent method for regulating gas temperature, (ii) designing the adaptive algorithms and corrective links with differentiators implementation to control parameters dynamic adjustment for eliminating the time

discrepancy between the required and actual values. Finally, it's expected to increase the system's static and dynamic accuracy and improve its stability, as well as reduce the engine stabilization time.

4. Materials and Methods

4.1. Development of an intelligent gas temperature controller

The proposed controller (Figure 1) is based on a double summation circuit [18]. It is based on a comparative analysis of signals received from thermocouples and a gas-generator rotor speed sensor [23], using an inertial link, a comparison element, and a nonlinear unit for adjusting the fuel supply. This ensures compensation for the delay in heating up the turbine and the temperature regime stabilization. Under normal conditions, the signals from the speed sensor compensate for each other, and when the regime changes abruptly, a correcting pulse appears, leading to a change in fuel consumption proportional to the largest deviation in the summing amplifiers. Under transient conditions, the signal delay through the inertial link leads to the different signal appearance in the comparison element, which is then amplified through the summing devices. The control channel selector selects the largest received deviations, and the nonlinear element with an exponential or parabolic characteristic reduces the specified temperature setting, compensating for the delay in heating up the compressor turbine blades.

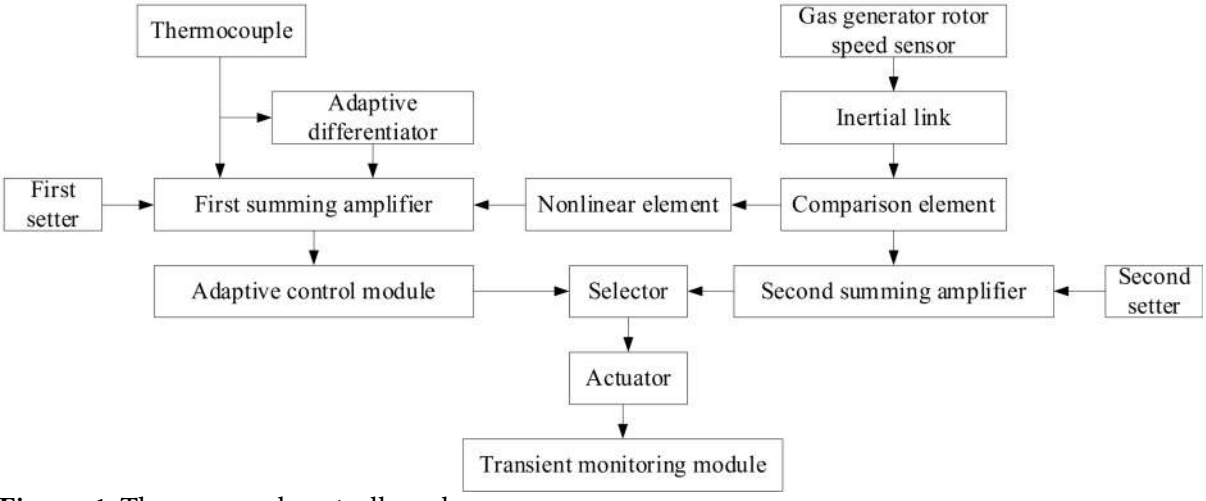


Figure 1: The proposed controller scheme

The proposed scheme for the helicopter TE gas temperature regulating integrates adaptive algorithms and correcting links with differentiators, which allows for dynamic optimization of control parameters and time discrepancies elimination between required and actual values. Adaptive algorithms analyze the transient processes current dynamics and correct the gain factors and inertial links time constants in real time, thus providing a more accurate and timely response to changes in the engine operating mode. The integration of differentiators into measuring circuits allows for predicting trends in temperature conditions, compensating for the delay in turbine warm-up, and a nonlinear element with an exponential characteristic synchronizes system responses, minimizing sharp transient fluctuations. The result is an ACS of adapting to changing operating conditions, increasing the helicopter TE reliability and efficiency.

The proposed controller features include the adaptive control module introduction, which is connected between the summing amplifiers and the control channel selector. This module performs the transmission coefficients real-time correction and the inertial links time constants, responding to the transient processes dynamics and eliminating the time discrepancy between the specified and actual parameters. The adaptive differentiator introduction integrated into the measuring circuit between the thermocouple unit and the first summing amplifier facilitates preliminary signal processing, predicting temperature change trends, and compensating for the delay in heating the compressor turbine blades. The proposed controller also includes a transient mode monitoring unit connected to the actuator to form feedback and dynamically optimize the control algorithms.

Thus, the scientific novelty consists in obtaining further development of the helicopter TE gas temperature controller according to the double summation scheme, which, due to the adaptive

algorithm's introduction integrated with corrective links equipped with differentiators, allows control parameters, real-time optimization, and inertial delays compensation of measuring sensors. This ensures synchronization between the required and actual temperature modes, significantly increasing the helicopter TE accuracy, stability, and efficiency.

4.2. Development of the intelligent method for regulating gas temperature

Based on [17, 18, 23, 24], it is assumed that the gas temperature dynamics is described by the following equation with a delay of the form:

$$\dot{T}(t)=a\cdot T(t)+b\cdot u(t-\tau)+d(t), \tag{1}$$

where $T(t)$ is the gas temperature at time t, $u(t)$ is the control action (for example, change in fuel consumption), a and b are the system coefficients, τ is the measuring inertial delay or actuator links, and $d(t)$ is the external disturbance.

To track the given temperature trajectory $T_{ref}(t)$, we define the control error:

$$e(t) = T_{ref}(t) - T(t). \tag{2}$$

The delayed system transfer function based on the Padé approximation [25] for exponential delay is:

$$e^{-\tau\cdot t}\approx\frac{1-\frac{\tau}{2}\cdot s}{1+\frac{\tau}{2}\cdot s}, \tag{3}$$

from where the system transfer function has the form:

$$G(s)=\frac{b\cdot\left(1-\frac{\tau}{2}\cdot s\right)}{(s-a)\cdot\left(1+\frac{\tau}{2}\cdot s\right)}. \tag{4}$$

To compensate for the measurement delay, an adaptive observer is used that estimates the system state. Let the observer have the form:

$$\hat{\dot{T}}(t)=a\cdot\hat{T}(t)+b\cdot u(t)+K_{obs}\cdot\left(T(t)-\hat{T}(t)\right), \tag{5}$$

where $\hat{T}$ is the temperature estimate and K_{obs} is the observation coefficient (can be chosen as a vector for more complex models, for example, as in [26, 27]).

To compensate for the delay τ, the state prediction at time $t + \tau$ is used using a Taylor series expansion of the form:

$$\hat{T}(t+\tau)=\hat{T}(t)+\tau\cdot\hat{\dot{T}}(t)+\frac{\tau^2}{2}\cdot\hat{\ddot{T}}(t)+\ldots \tag{6}$$

In practical implementation, one can limit oneself to the first or second term of the expansion, as shown, for example, in [16, 18]. To estimate the temperature's second derivative, a difference scheme of the form is used:

$$\hat{\ddot{T}}(t)\approx\frac{T(t)-2\cdot T(t-\Delta t)+T(t-2\cdot\Delta t)}{\Delta t^2}. \tag{7}$$

Based on the adaptive observer mathematical model (5) and the state prediction method (6), an intelligent control law is proposed that takes into account the predicted error:

$$u(t)=k_1(t)\cdot\left(T_{ref}(t)-\hat{T}(t+\tau)\right)+k_2(t)\cdot\dot{T}_{ref}(t)+k_3(t)\cdot\int_0^t\left(T_{ref}(s)-\hat{T}(s+\tau)\right)ds, \tag{8}$$

where $k_1(t)$ is the proportional coefficient, $k_2(t)$ is the differential gain coefficient, $k_3(t)$ is the integral gain coefficient, $\dot{T}_{ref}(t)$ is the given trajectory derivative.

The coefficients $k_i(t)$ are adjusted in real time using adaptive laws, for example, according to the gradient descent scheme:

$$\dot{k}_i(t)=-\gamma_i\cdot e(t)\cdot\phi_i(t), (i = 1, 2, 3, \ldots \tag{9}$$

where $\gamma_i > 0$ are the adaptation rates, $\phi_i(t)$ are the signal functions depending on the system's current state, for example, $\phi_1(t) = T_{ref}(t) - \hat{T}(t+\tau)$, $\phi_2(t) = \dot{T}_{ref}(t)$ and $\phi_2(t) = \int_0^t \left(T_{ref}(s) - \hat{T}(s+\tau)\right) ds$.

To determine the optimal parameters, the quality functional can be minimized:

$$J = \int_t^{t+T_p} \left(Q \cdot \left(T(s) - T_{ref}(s)\right)^2 + R \cdot \left(u(s)\right)^2\right) ds, \tag{10}$$

where $Q, R > 0$ are the weighting coefficients, T_p is the predict horizon.

To improve the compensation accuracy for inertial delays, it is proposed to implement a neural network module [28–30] that corrects the delay estimate:

$$\hat{\tau}(s) = \tau_0 + f_{NN}(\varphi(t)), \tag{11}$$

where τ_0 is the delay base value, $f_{NN}(\bullet)$ is the neural network approximating function, and $\varphi(t)$ is the feature vector (for example, gas generator rotor speed, current temperature dynamics, and other parameters).

Thus, the scientific novelty of the developed intelligent method lies in the adaptive observer with state prediction implementation and a neural network module for compensating for inertial delays, which allows for the control parameters real-time optimization.

Within the developed method framework, theorem 1, "On adaptive stability and convergence of a closed system of intelligent gas temperature control with inertial delays compensation," is formulated. According to the developed intelligent method, the system dynamics is given by the equation $\dot{T}(t) = a \cdot T(t) + b \cdot u(t-\tau) + d(t)$ provided that the disturbances $d(t)$ are bounded and the adaptive observer has the form $\dot{\hat{T}}(t) = a \cdot \hat{T}(t) + b \cdot u(t) + K_{obs} \cdot \left(T(t) - \hat{T}(t)\right)$, in this case, the control action is determined by the law $u(t) = k_1(t) \cdot \left(T_{ref}(t) - \hat{T}(t+\tau)\right) + k_2(t) \cdot \dot{T}_{ref}(t) + k_3(t) \cdot \int_0^t$ ¿¿ $- \hat{T}(s+\tau)\big) ds$, and the adaptive coefficients change as $\dot{k}_i(t) = -\gamma_i \cdot e(t) \cdot \phi_i(t)$, ($i$ = 1, 2, 3, ...). If there exists a Lyapunov function of the form $V(t) = \frac{1}{2} \cdot \left(e(t)\right)^2 + \sum_{i=1}^{3} \frac{1}{2 \cdot \gamma_i} \cdot \left(k_i(t) - k_i^{¿}(t)\right)^2$, where $k_i^{¿}$ are the coefficient's optimal values, and if for some α, $\beta > 0$ the inequality holds $\dot{V}(t) \le \alpha \cdot V(t) + \beta \cdot \left\|d(t)\right\|^2$, then the closed system is uniformly bounded in finite time, and the tracking error $e(t) = T_{ref}(t) - T(t)$ asymptotically tends to an arbitrarily small neighborhood of zero, provided that the perturbations $d(t)$ are sufficiently small.

Proof of Theorem 1.

Let us consider a candidate for a Lyapunov function of the form

$$V(t) = \frac{1}{2} \cdot \left(e(t)\right)^2 + \sum_{i=1}^{3} \frac{1}{2 \cdot \gamma_i} \cdot \left(\tilde{k}_i(t)\right)^2, \tag{12}$$

where

$$e(t) = T_{ref}(t) - T(t),\ \tilde{k}_i(t) = k_i(t) - k_i^{¿}(t)\ (i = 1, 2, 3, \ldots), \tag{13}$$

and $k_i^{¿}$ are the coefficient's optimal (constant) values, and $\gamma_i > 0$ are the adaptation constants.

Differentiate $V(t)$ with respect to time:

$$\dot{V}(t) = e(t) \cdot \dot{e}(t) + \sum_{i=1}^{3} \frac{1}{\gamma_i} \cdot \tilde{k}_i(t) \cdot \dot{\tilde{k}}_i(t), \tag{14}$$

Since $k_i^{¿}$ are constant, then $\dot{k}_i^{¿}(t) = \dot{k}_i^{¿}$. Taking into account the adaptation law (9), we obtain:

$$\dot{V}(t) = e(t) \cdot \dot{e}(t) - \sum_{i=1}^{3} \tilde{k}_i(t) \cdot e(t) \cdot \phi_i(t). \tag{15}$$

Since the gas temperature dynamics is given by equation (1), and the control action is selected according to the law (8) using the adaptive observer (5) and under the correct delay compensation

condition (using the state prediction according to the Taylor series) (6), it can be shown that the error dynamics $e(t) = T_{ref}(t) - T(t)$ in a closed system approximately takes the form

$$\dot{e}(t) = -\sum_{i=1}^{3} k_i^{\cdot} \cdot e(t) + \delta(t), \tag{16}$$

where $\delta(t)$ combines model errors, delay compensation and external disturbances, and $\phi_i(t)$ are signal functions that depend on the system's state.

When substituting (16) into (15) we obtain:

$$\dot{V}(t) = e(t) \cdot \left(-\sum_{i=1}^{3} k_i^{\cdot} \cdot e(t) + \delta(t) \right) - \sum_{i=1}^{3} \tilde{k}_i(t) \cdot e(t) \cdot \phi_i(t). \tag{17}$$

Let's group the terms:

$$\dot{V}(t) = -(e(t))^2 \cdot \sum_{i=1}^{3} k_i^{\cdot} \cdot \phi_i(t) - e(t) \cdot \sum_{i=1}^{3} \tilde{k}_i(t) \cdot \phi_i(t) + e(t) \cdot \delta(t). \tag{18}$$

Note that

$$\sum_{i=1}^{3} \left(k_i^{\cdot} + \tilde{k}_i(t) \right) \cdot \phi_i(t) = \sum_{i=1}^{3} k_i(t) \cdot \phi_i(t), \tag{19}$$

and with the $\phi_i(t)$ and $k_i(t)$ correct choice it is assumed that the total term $\sum_{i=1}^{3} k_i(t) \cdot \phi_i(t)$ is a positive definite function, that is, there exists $\lambda > 0$ such that

$$\sum_{i=1}^{3} k_i(t) \cdot \phi_i(t) \geq \lambda > 0. \tag{20}$$

Thus, the assessment can be written as:

$$\dot{V}(t) = -\lambda \cdot (e(t))^2 + e(t) \cdot \delta(t). \tag{21}$$

We use Yong's inequality:

$$e(t) \cdot \delta(t) \leq \frac{\lambda}{2} \cdot (e(t))^2 + \frac{1}{2 \cdot \lambda} \cdot (\delta(t))^2. \tag{22}$$

Hence,

$$\dot{V}(t) \leq -\lambda \cdot (e(t))^2 + \frac{\lambda}{2} \cdot (e(t))^2 + \frac{1}{2 \cdot \lambda} \cdot (\delta(t))^2 = \frac{-\lambda}{2} \cdot (e(t))^2 + \frac{1}{2 \cdot \lambda} \cdot (\delta(t))^2. \tag{23}$$

Taking into account that the function $V(t)$ satisfies the inequality

$$V(t) \geq \frac{1}{2} \cdot (e(t))^2, \tag{24}$$

the final assessment was received:

$$\dot{V}(t) \leq -\lambda \cdot V(t) + \frac{1}{2 \cdot \lambda} \cdot (\delta(t))^2. \tag{25}$$

Denoting $\alpha = \lambda$ and $\beta = \frac{1}{2 \cdot \lambda}$, then

$$\dot{V}(t) \leq -\alpha \cdot V(t) + \beta \cdot \|\delta(t)\|^2. \tag{26}$$

According to the comparison lemma, if $\dot{V}(t) \leq -\alpha \cdot V(t) + \beta \cdot \|\delta(t)\|^2$, then the function $V(t)$ has the uniform finite boundedness property, that is, there exists a constant V_∞ such that

$$\limsup_{t \to \infty} V(t) \leq \frac{\beta}{\alpha} \cdot^{\cdot} t \geq 0 \|\delta(t)\|^2. \tag{27}$$

Since $V(t)$ includes the term $\frac{1}{2} \cdot \left(e(t)\right)^2$, this means that the error $e(t)$ asymptotically approaches a zero neighborhood whose size is determined by the quantity $¿_{t \geq 0} \left\|\delta(t)\right\|$. Provided that the disturbances and delay compensation errors are sufficiently small, this neighborhood can be made arbitrarily small.

Thus, it is proved that the closed system with the chosen adaptive control law and the coefficient adaptation law is uniformly finitely determined, and the tracking error $e(t) = T_{ref}(t) - T(t)$ asymptotically tends to an arbitrarily small neighborhood of zero. This means

$$\dot{V}(t) \leq -\alpha \cdot V(t) + \beta \cdot \left\|\delta(t)\right\|^2 \Rightarrow \limsup_{t \to \infty} V(t) \leq \frac{\beta}{\alpha} \cdot ¿ t \geq 0 \left\|\delta(t)\right\|^2,$$

which proves the theorem on adaptive stability and convergence.

4.3. Development of a neural network module for delay estimation correction

Based on [31–33], we propose to use a deep fully connected (feedforward) neural network to approximate the function $f_{NN}(\varphi(t))$ (Figure 2). The neural network architecture is defined by an input layer of dimension n, where $\varphi(t) \in \mathbb{R}^n$, followed by one or more hidden layers with nonlinear activation functions; in particular, for the two-layer MLP architecture example [34], the first hidden layer contains m_1 neurons, and the second contains m_2 neurons, after which the output layer, consisting of one neuron with linear activation, forms the correction value.

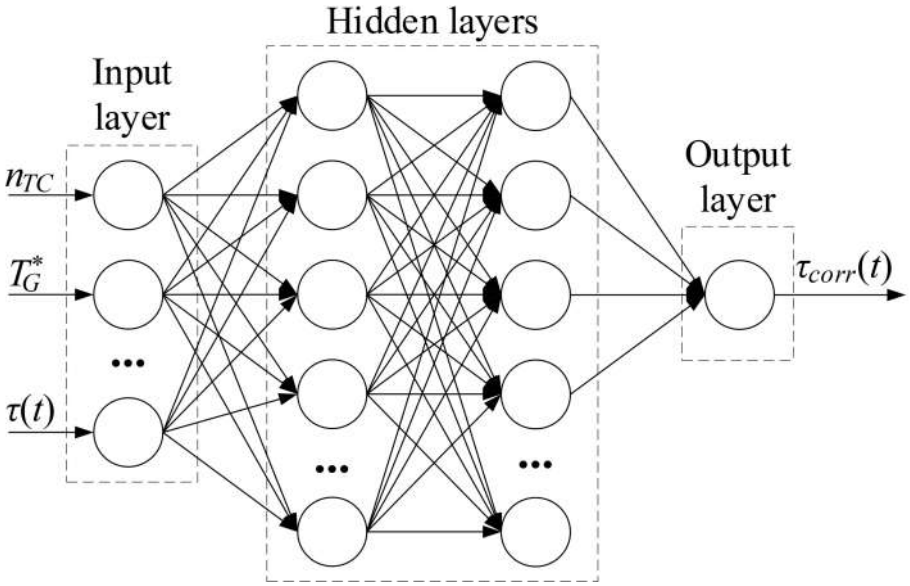


Figure 2: Architecture of the proposed deep fully connected (feedforward) neural network

In the general case, for a neural network with L layers (excluding the input), the input is initialized as $a^{(0)} = \varphi(t)$. For each hidden layer $l = 1, \ldots, L - 1$, the calculation is performed:

$$z^{(l)} = W^{(l)} \cdot a^{(l-1)} + b^{(l)}, \tag{28}$$

$$a^{(l)} = \sigma^{(l)} \cdot \left(z^{(l)}\right), \tag{29}$$

where $W^{(l)}$ is the weight matrix, $b^{(l)}$ is the bias vector, and $\sigma^{(l)}(\bullet)$ is the activation function (e.g. ReLU, SmoothReLU [35], tanh, or sigmoid).

At the output layer ($l = L$) the following is calculated:

$$z^{(l)} = W^{(L)} \cdot a^{(L-1)} + b^{(L)}, \tag{30}$$

$$f_{NN}\left(\varphi(t)\right) = W^{(L)} \cdot a^{(L)} = z^{(L)}, \tag{31}$$

where a linear activation function is used since the problem is a regression problem.

Thus, the delay adjustment module has the form:

$$\tau_{corr}(t) = \tau_0 + z^{(L)}. \tag{32}$$

In this research, we propose the neural network architecture with two hidden layers use (Figure 2), for which the presented expressions will have the form presented in Table 1.

Table 1

Basic analytical expressions for the applied neural network

Number	Layer	Analytical expression
1	First hidden layer (l = 1)	$z^{(1)} = W^{(1)} \cdot \varphi(t) + b^{(1)}, a^{(1)} = Smooth\,ReLU^{(1)}\left(z^{(1)}\right)$
2	Second hidden layer (l = 2)	$z^{(2)} = W^{(2)} \cdot a^{(1)} + b^{(2)}, a^{(2)} = Smooth\,ReLU^{(2)}\left(z^{(2)}\right)$
3	Output layer (l = 3)	$z^{(3)} = W^{(3)} \cdot a^{(2)} + b^{(3)}, f_{NN}(\varphi(t)) = z^{(3)}$
4	Final delay estimate	$\tau_{corr}(t) = \tau_0 + z^{(3)}$

To determine the parameters $\Theta = \left\{W^{(l)}, b^{(l)}\right\}_{l=1}^{L}$, the neural network is trained on historical data, where for each time moment t_i the feature vector $\varphi(t_i)$ and the actual delay τactual(t_i) are known. The training task is to minimize the loss function, for example, the mean square error (MSE), as shown in [36, 37]:

$$L(\Theta) = \frac{1}{2 \cdot N} \cdot \sum_{i=1}^{N} \left(\tau_{actual}(t_i) - \left(\tau_0 + f_{NN}(\varphi(t_i))\right)\right)^2 + \lambda \cdot \sum_{l=1}^{L} \left(W^{(l)}\right)_2^2, \quad (33)$$

where $\lambda > 0$ is the regularization coefficient [36].

The neural network parameters are updated according to the gradient descent rule:

$$\Theta \leftarrow \Theta - \eta \cdot \nabla_{\Theta} L(\Theta), \quad (34)$$

where $\eta > 0$ is the training rate.

At the same time, gradients are calculated at each layer using backpropagation. For example, for the last layer, the error at the output layer is calculated as:

$$\delta^{(L)} = \frac{\partial L}{\partial z^{(L)}} = a^{(L)} - \left(\tau_{actual} - \tau_0\right). \quad (35)$$

For each previous layer $l = L - 1, L - 2, \ldots, 1$ the following is determined:

$$\delta^{(l)} = W^{(l+1)T} \odot \sigma'^{(l)}\left(z^{(l)}\right), \quad (36)$$

where $\odot$ denotes element-wise multiplication and $\sigma'^{(l)}$ is the activation function derivative.

The weights and biases update for the l-th layer is performed as:

$$W^{(l)} = W^{(l)} - \eta \cdot \delta^{(l)}\left(a^{(l-1)}\right)^T, \quad (37)$$

$$b^{(l)} = b^{(l)} - \eta \cdot \delta^{(l)}. \quad (38)$$

The resulting delay estimate $\tau_{corr}(t)$ is used to correct the control action in the control scheme. If the control law (8) was previously written as

$$u(t) = k_1(t) \cdot e(t) + k_2(t) \cdot \dot{e}(t) + k_3(t) \cdot \int e(t)\,dt, \quad (39)$$

then, taking into account the delay correction, it can be supplemented as follows. For example, the parameter $\tau_{corr}(t)$ can be taken into account when predicting the state through the expansion in a Taylor series:

$$\hat{T}\left(t + \tau_{corr}(t)\right) = \hat{T}(t) + \tau_{corr}(t) \cdot \hat{\dot{T}}(t) + \frac{1}{2} \cdot \hat{\ddot{T}}(t) \cdot \left(\tau_{corr}(t)\right)^2 + \ldots \quad (40)$$

Thus, the neural network module for correcting the delay estimate is implemented according to the scheme $\tau_{corr}(t) = \tau_0 + f_{NN}(\varphi(t))$, where the function $f_{NN}(\varphi(t))$ is approximated by a neural network constructed according to the scheme (27)–(32). The module is trained by minimizing MSE (33) with updating the parameters according to (34)–(38). When integrated into the general control algorithm, the $\tau_{corr}(t)$ value is used to accurately predict the system state (20), which significantly improves the control quality in the inertial delays presence.

5. Case study

5.1. Results of the helicopter turboshaft engine gas temperature control channel with the two value's algebraic minimum selector research

It is accepted that, in general, the proposed intelligent gas temperature controller (Figure 3) is a two-channel controller: the gas temperature in front of the compressor turbine regulating channel and the gas generator rotor speed regulating channel [23, 38] (the free turbine rotor speed regulating channel [39] is not taken into account).

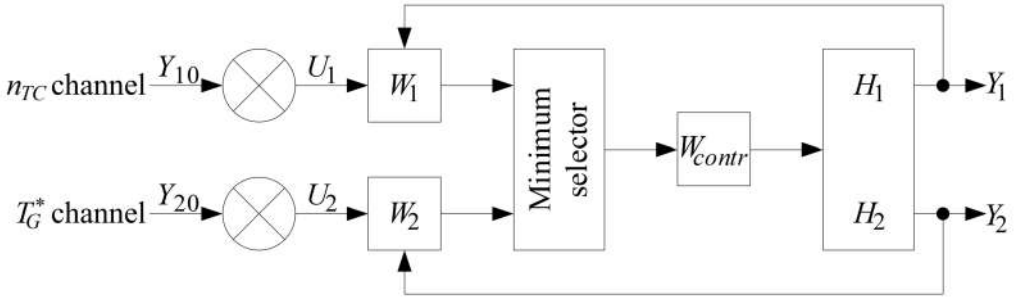


Figure 3: Proposed intelligent controller circuit

According to Figure 3, the minimum selector is described by the expression:

$$U=\begin{cases}U_1, U_1 \le U_2,\\ U_2, U_1 > U_2,\end{cases} \tag{41}$$

where H_1 is the object's (engine TV3-117) transfer function in the first control channel (the gas generator rotor speed channel) $H_1=\frac{1}{T\cdot s}$, H_2 is the object's (engine TV3-117) transfer function in the second channel (the gas temperature in front of the compressor turbine channel) $H_2 = 1$, where:

$$W_{contr}=\frac{k_{contr}}{s\cdot(\tau\cdot s+1)},\ W_1 = k_1,\ W_2 = k_2, \tag{42}$$

where Y_{10} and Y_{20} are constant settings.

Let's consider the individual open channel's transfer functions:

$$W_I(s)=\frac{k_1\cdot k_{contr}}{s\cdot(T\cdot s+1)\cdot(\tau\cdot s+1)}, \tag{43}$$

$$W_I(j\omega)=\frac{k_1\cdot k_{contr}}{j\omega\cdot(T\cdot j\omega+1)\cdot(\tau\cdot j\omega+1)}=\frac{k_1\cdot k_{contr}}{-(\tau+T)\cdot\omega^2+j\omega\cdot(1-\tau\cdot T\cdot\omega^2)}=¿$$
$$¿\frac{k_1\cdot k_{contr}\cdot(\tau+T)^2\cdot\omega^4}{(\tau+T)\cdot\omega^4+\omega^2\cdot(1-\tau\cdot T\cdot\omega^2)^2}-j\cdot\frac{k_1\cdot k_{contr}\cdot(1-\tau\cdot T\cdot\omega^2)}{(\tau+T)\cdot\omega^4+\omega^2\cdot(1-\tau\cdot T\cdot\omega^2)^2}, \tag{44}$$

$$W_I(s)=\frac{k_2\cdot k_{contr}}{s\cdot(\tau\cdot s+1)}, \tag{45}$$

$$W_{II}(j\omega)=\frac{k_2\cdot k_{contr}}{-\tau\cdot\omega^2+j\omega}=\frac{k_2\cdot k_{contr}\cdot\tau\cdot\omega^2}{\tau^2\cdot\omega^4+\omega^2}-j\cdot\frac{k_2\cdot k_{contr}\cdot\omega}{\tau^2\cdot\omega^4+\omega^2}, \tag{46}$$

where $k_1 = 10$, $k_2 = 1$, $k_p = 10$, $T = 0.5$ second, $\tau = 0.025$ second [37, 38].

Then the proposed two-channel intelligent controller's transfer function will have the form:

$$\Phi(s)=\frac{W_I(s)-W_{II}(s)}{2+W_I(s)+W_{II}(s)}=\frac{k_1\cdot k_{contr}-k_2\cdot k_{contr}\cdot(T\cdot s+1)}{2\cdot(T\cdot s+1)\cdot(T\cdot s+1)\cdot s+k_1\cdot k_{contr}+k_2\cdot k_{contr}\cdot(T\cdot s+1)} \tag{47}$$

$$\Phi(j\omega)=\frac{\left(k_1\cdot k_{contr}-k_2\cdot k_{contr}\right)-j\cdot k_2\cdot k_{contr}\cdot T\cdot\omega}{k_1\cdot k_{contr}-k_2\cdot k_{contr}-2\cdot k_2\cdot k_{contr}\cdot T\cdot\omega^2+j\cdot\left(\left(2+k_2\cdot k_{contr}\cdot T\right)\cdot\omega-2\cdot T\cdot\tau\cdot\omega^3\right)}=$$

$$=\frac{\left(k_1\cdot k_{contr}-k_2\cdot k_{contr}\right)-k_2\cdot k_{contr}\cdot T\cdot\omega}{\left(k_1\cdot k_{contr}-k_2\cdot k_{contr}-2\cdot k_2\cdot k_{contr}\cdot T\cdot\omega^2\right)^2+\left(\left(2+k_2\cdot k_{contr}\cdot T\right)\cdot\omega-2\cdot T\cdot\tau\cdot\omega^3\right)^2}- \quad (48)$$

$$-j\cdot\frac{\left(k_1\cdot k_{contr}-k_2\cdot k_{contr}\right)\cdot\left(\left(2+k_2\cdot k_{contr}\cdot T\right)\cdot\omega-2\cdot T\cdot\tau\cdot\omega^3\right)+k_2\cdot k_{contr}\cdot T\cdot\omega\cdot\left(k_1\cdot k_{contr}-k_2\cdot k_{contr}-2\cdot k_2\cdot k_{contr}\cdot T\cdot\omega^2\right.}{\left(k_1\cdot k_{contr}-k_2\cdot k_{contr}-2\cdot k_2\cdot k_{contr}\cdot T\cdot\omega^2\right)^2+\left(\left(2+k_2\cdot k_{contr}\cdot T\right)\cdot\omega-2\cdot T\cdot\tau\cdot\omega^3\right)^2}$$

The Nyquist hodographs constructed for the system's individual loops with the values $k_1 = 10$, $k_2 = 1$, $k_{contr} = 10$, $T = 0.5$ second, $\tau = 0.025$ second [23, 38] demonstrate that in this automatic control system with a minimum selector, the closed loop $W_{\text{I}}(s)$ is unstable, while the closed loop $W_{\text{II}}(s)$ is stable (Figure 4).

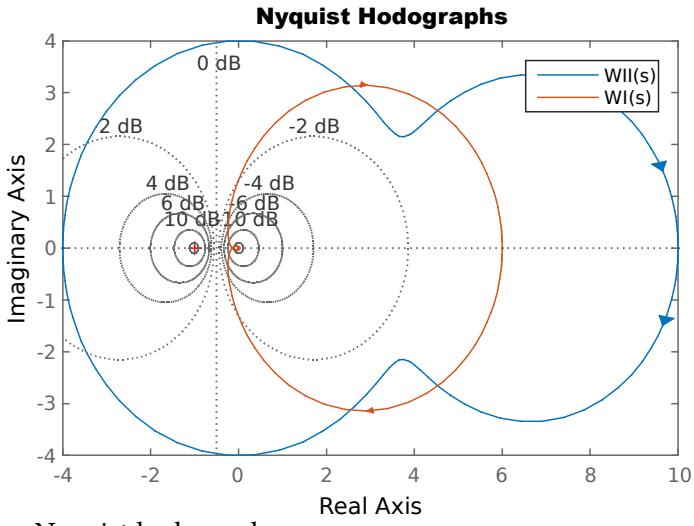


Figure 4: The resulting Nyquist hodographs

The transformed system's $\Phi(s)$ linear link amplitude-phase characteristic is shown in Figure 5. The condition for the oscillation's occurrence in such a nonlinear system is the equivalent linear part's $\Phi(s)$ hodograph's intersection point with the complex nonlinearity coefficient's hodograph. In this case, the latter corresponds to the negative segment of the real axis in the range from −1 to −∞. It follows from this those oscillations with a frequency of $\omega \approx 12.227$ s^{-1} ($f \approx 1.96$ Hz) can occur in this system.

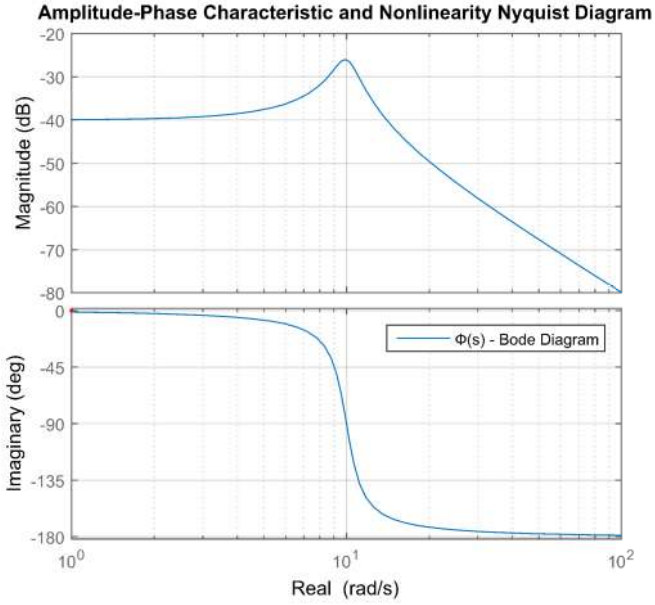


Figure 5: The transformed system's linear link's resulting amplitude-phase characteristic

In this research, the system's behavior in the time domain was analyzed. For this aim, the controller links were presented using differential equations:

$$W(s)=\frac{1}{\tau\cdot s+1}=\frac{U_{out}}{U_{¿}},\ U_{¿}(s)=T\cdot\frac{dU_{out}(s)}{dt}+U_{out}(s),\ \text{or}$$

$$\frac{dU_{out}(s)}{dt}=\frac{1}{T}\cdot U_{¿}-\frac{1}{T}\cdot U_{out}, \tag{49}$$

$$W(s)=\frac{k_{contr}}{s\cdot(\tau\cdot s+1)}=\frac{U_{out}}{U_{¿}},\ \tau\cdot\frac{d^2U_{out}(s)}{dt^2}+\frac{dU_{out}(s)}{dt}=k_{contr}\cdot U_{¿}.$$

Therefore, this system is characterized by two differential equations set and an equation that determines the selector switching:

$$\begin{cases}\dfrac{dx}{dt}=\dfrac{Z}{T}-\dfrac{x}{T},\\ \tau\cdot\dfrac{d^2Z}{dt^2}+\dfrac{dZ}{dt}=k_{contr}\cdot U,\end{cases} \tag{50}$$

$$U=\begin{cases}U_1, U_1-U_2\le 0,\\ U_2, U_1-U_2>0.\end{cases} \tag{51}$$

The system remains stable when the condition is met: $Y_{10} = 1$, $Y_{20} < 1$ (if $Y_{20} > 1$, oscillations occur). In this region, the output variables change exponentially. The second circuit is closed (Figure 3), and Y_2 reaches the steady-state value in $t_{contr} = 0.25...0.3$ seconds. At the setpoint value $Y_{20} > 1$, oscillations occur in the system that do not damp. Their frequency remains unchanged and is $f \approx 1.96$ Hz; $T = 0.427$ seconds. The oscillation's amplitude increases as the setpoint increases.

To eliminate temperature overload, corrective elements are introduced [40]. The selection condition is determined by the following expression [40, 41]:

$$U_{n_{TC}}=U_{T_G^{¿}}. \tag{52}$$

In this research, two selection options were considered, similar to [41]:

$$\varepsilon_2 = Y_{20} - Y_2 = 0, \tag{53}$$

$$\varepsilon_1 = \varepsilon_2. \tag{54}$$

In this research, the correcting link's $W_{k1}(s)$ and $W_{k2}(s)$ transfer functions are determined based on the selection conditions. For the first condition (53):

$$U_{n_{TC}}=W_{n_{TC}}(s)\cdot\varepsilon_1, \tag{55}$$

$$U_{T_G^{¿}}=W_{T_G^{¿}}(s)+W_{k1}(s)\cdot W_{T_G^{¿}}(s)\cdot s+W_{k2}(s)\cdot W_{T_G^{¿}}(s)\cdot\varepsilon_2. \tag{56}$$

From the selection condition (52):

$$W_{n_{TC}}(s)\cdot\varepsilon_1-W_{T_G^{¿}}(s)+W_{k1}(s)\cdot W_{T_G^{¿}}(s)\cdot s+W_{k2}(s)\cdot W_{T_G^{¿}}(s)\cdot\varepsilon_2, \tag{57}$$

if

$$W_{n_{TC}}(s)=W_{k1}(s)\cdot W_{T_G^{¿}}(s), \tag{58}$$

and

$$W_{T_G^{¿}}(s)+W_{k1}(s)\cdot W_{T_G^{¿}}(s)=1, \tag{59}$$

then $\varepsilon_2 = 0$.

Then

$$W_{k1}(s)=\frac{W_{n_{TC}}(s)}{W_{T_G^{¿}}(s)}, \tag{60}$$

$$W_{k2}(s)=\frac{1-W_{T_G^{¿}}(s)}{W_{T_G^{¿}}(s)}, \tag{61}$$

For the second condition (54) expressions (55) – (57) are valid and if

$$W_{n_{TC}}(s)-W_{k1}(s)\cdot W_{T_G^i}(s)=1, \tag{62}$$

$$W_{T_G^i}(s)-W_{k2}(s)\cdot W_{T_G^i}(s)=1, \tag{63}$$

$$W_{k1}(s)=\frac{W_{n_{TC}}(s)-1}{W_{T_G^i}(s)}, \tag{64}$$

$$W_{k2}(s)=\frac{1-W_{T_G^i}(s)}{W_{T_G^i}(s)}. \tag{65}$$

For modeling and calculations in this study, the parameters of the TV3-117 engine, which is the Mi-8MTV helicopter's power plant's part, were used [42]:

$$(0.21\cdot s+1)\cdot x_{n_{TC}}=(0.229\cdot s+1.306)\cdot x_{G_T}, \tag{66}$$

$$(0.064\cdot s^2+0.667\cdot s+1)\cdot x_{T_G^i}=(0.522\cdot s+3)\cdot x_{G_T}, \tag{67}$$

where $x_{n_{TC}}$ is the output signal for the turbocharger rotor speed, $x_{T_G^i}$ is the output signal for the gas temperature in front of the compressor turbine, x_{G_T} is the input signal for fuel consumption.

From (66), (67) the gas generator rotor speed $W_{n_{TC}}^{G_T}$ and the gas temperature in front of the compressor turbine $W_{T_G^i}^{G_T}$ transfer functions are obtained, identical to those in [38]:

$$W_{n_{TC}}^{G_T}(s)=\frac{0.229\cdot s+1.306}{0.21\cdot s+1}, \tag{68}$$

$$W_{T_G^i}^{G_T}(s)=\frac{0.522\cdot s+3}{0.064\cdot s^2+0.667\cdot s+1}. \tag{69}$$

From (67) and (68) it follows that the gas generator rotor speed controllers $W_{n_{TC}}(s)$ and the gas temperature in front of the compressor turbine $W_{T_G^i}(s)$ transfer functions have the form:

$$W_{n_{TC}}(s)=\frac{1}{0.229\cdot s+1.306}, \tag{70}$$

$$W_{T_G^i}(s)=\frac{1}{0.522\cdot s+3}. \tag{71}$$

Then, according to (60), (61), (64), (65), the first and second correction links $W_{k1}(s)$ and $W_{k2}(s)$ transfer functions are obtained, respectively, for conditions (53) (*I*) and (54) (*II*):

$$W_{k1}^{(I)}(s)=\frac{0.522\cdot s+3}{0.229\cdot s+1.306}, \tag{72}$$

$$W_{k2}^{(I)}(s)=0.522\cdot s+2, \tag{73}$$

$$W_{k1}^{(II)}(s)=\frac{0.12\cdot s^2+0.847\cdot s+0.918}{0.229\cdot s+1.306}, \tag{74}$$

$$W_{k2}^{(I)}(s)=0.522\cdot s+2. \tag{75}$$

It is noted that in [38], the analytical expressions describing the first and second correcting links $W_{k1}(s)$ and $W_{k2}(s)$ transfer functions have the form:

$$W_{k1}(s)=\frac{(-0.0018\cdot s+0.0517)\cdot(0.064\cdot s^2+0.667\cdot s+1)}{0.036\cdot s^2+0.38\cdot s+1}, \tag{76}$$

$$W_{k2}(s)=\frac{0.021\cdot s^2+0.048\cdot s-2}{0.174\cdot s+1}. \tag{77}$$

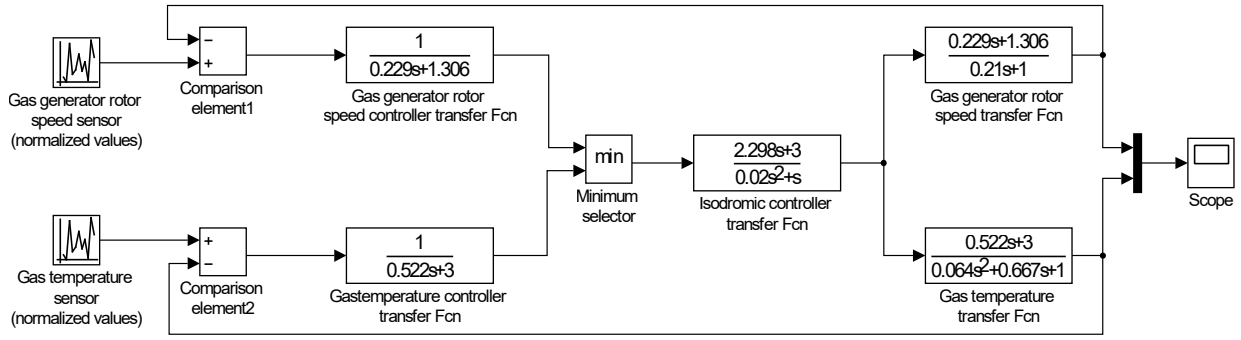
Thus, in the refined transfer functions $W_{k1}(s)$ and $W_{k2}(s)$ (72)–(75) compared to (76)–(77), a decrease in the variable s orders is observed, which allows eliminating high-order terms that increase the

system's dynamic sensitivity. In this case, only those terms are preserved that to the greatest extent determine the phase and amplitude characteristics necessary to compensate for inertial delays. The analysis shows that the dominant low-order terms (e.g., constant and linear in s) provide adequate delay suppression and maintenance of the required transient process, minimizing overshoot and stabilizing the ACS. This approach simplifies the correcting link's model, reduces the computational load and reduces the high-frequency noise amplification, which significantly increases the adaptability and reliability of the helicopter TE control system.

5.2. Modeling of the TV3-117 engine's gas temperature in front of the compressor turbine controller

According to Figure 3, the Matlab Simulink 2014b software package has constructed simulation schemes in two versions: without correction links (Figure 6a) and with correction links (Figure 6b). The simulation results are shown in Figure 7. It is noted that the actuator's (isodromic controller's) transfer function is adopted, according to [38], in the form:

$$W_{IC}(s)=\frac{3\cdot(0.56\cdot s+1)}{s\cdot(0.02\cdot s+1)}=\frac{1.68\cdot s+3}{0.02\cdot s^2+s}. \quad (78)$$



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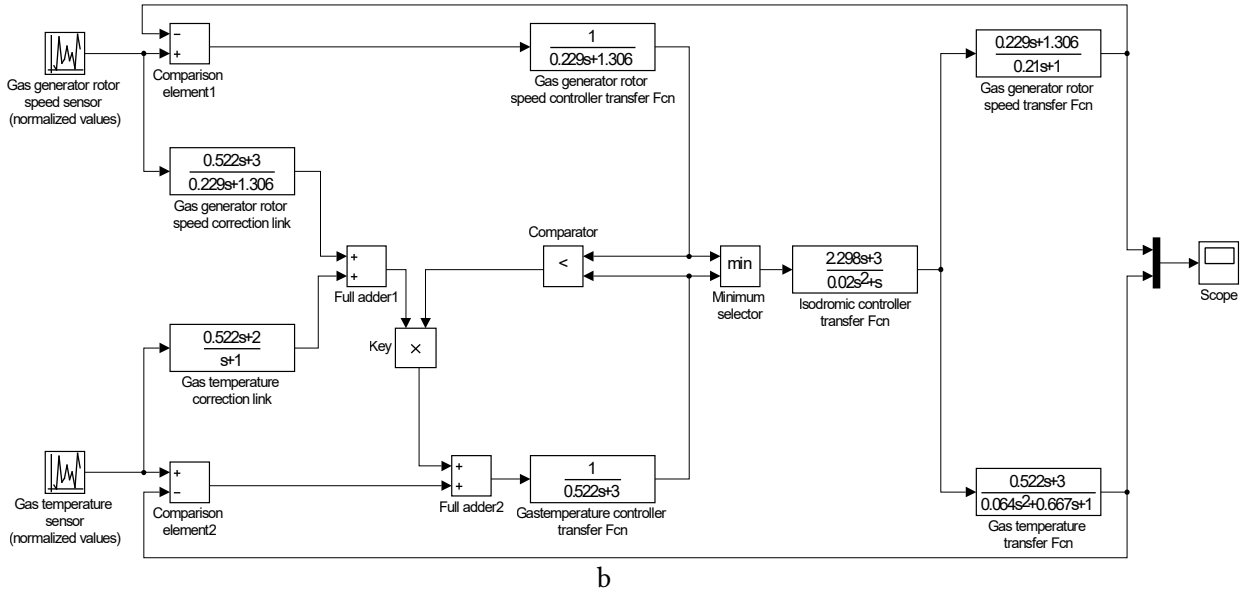
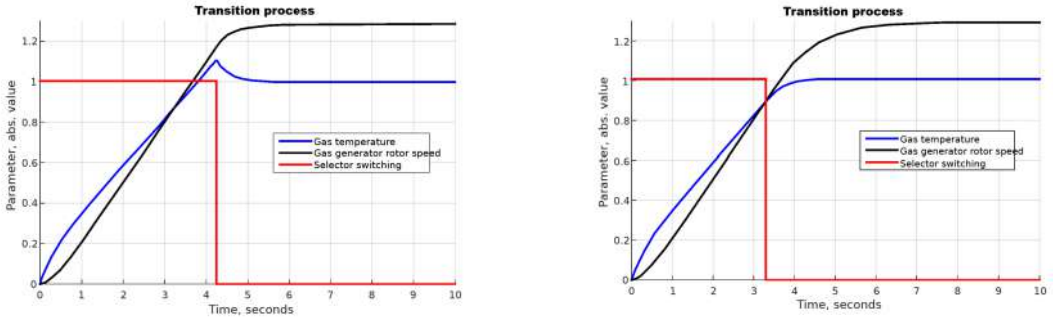


b

Figure 6: Developed schemes for modeling the gas temperature in front of the compressor turbine controller: (a) without correcting links; (b) with correcting links



a b

Figure 7: Resulting transient processes diagrams: (a) without correcting links; (b) with correcting links

In Figure 7, the blue curve corresponds to the gas temperature in front of the compressor turbine control channel, the black curve corresponds to the gas generator rotor speed control channel, and the red curve corresponds to the selector switching moment. The first diagram (Figure 7a) illustrates the transient process before the correction link's application: since the gas temperature in front of the compressor turbine controller has inertia with respect to the gas generator rotor speed controller, the selector switches with a delay, which leads to a temporary surge in the gas temperature transmission. To improve the dynamic accuracy of the system when changing the selector, it is necessary to introduce correction links, which is demonstrated in Figure 7b, where more efficient selection and the gas temperature channel connection is ensured, excluding the specified temperature mode excess. The transient processes qualitative characteristic's parameters can be quantitatively described as follows:

- The transient process's time interval (t_{trans}), reflecting the system's response speed and defined as the time interval from the dynamic changes beginning to the moment when the difference between the output signal and its new steady-state level becomes less than 5 % (for the first diagram (Figure 7a) t_{trans1} = 4.2 seconds, and for the second (Figure 7b) t_{trans2} = 3.3 seconds;
- Maximum excess in the transition period σ (overshoot), which is equal to:

$$\sigma = \frac{h(t)_{\text{setting}}(t)_{max}}{h_{\text{setting}}(t)} \tag{79}$$

For the first diagram (Figure 7a) $\sigma_1 = \frac{1.08-1}{1} \cdot 100\,\% = 8\,\%$. For the second diagram (Figure 7b) $\sigma_2 = \frac{1.015-1}{1} \cdot 100\,\% = 1.5\,\%$. Thus, the correction links with transfer functions (72)–(75) introduction makes it possible to virtually eliminate overshoot in the helicopter TE gas temperature in front of the compressor turbine control channel (the overshoot value does not exceed 1.5 %).

5.3. Test results of the neural network module for adjusting the delay estimation

During the research it was established that oscillations with a frequency of $f \approx 1.96$ Hz (the delay is 0.025 seconds) can occur in the developed controller. Therefore, it is advisable to conduct a delay dynamic's research in this frequency vicinity. For this aim, the Mi-8MTV helicopter flight tests results, the power plant of which consists of two TV3-117 engines [42], are used (the data for the left engine are used in the research). In response to an official request sent by the authors to the Ministry of Internal Affairs of Ukraine, information was obtained on the gas temperature in front of the compressor turbine (T_G^i) and the gas generator rotor speed (n_{TC}) in the nominal engine operating mode. The request was fulfilled within the research project "Theoretical and Applied Aspects of Aviation Sphere Development" (number 0123U104884) framework. The data was obtained based on the Mi-8MTV helicopter's flight tests. The experiments were conducted at an altitude of 2500 meters above sea level. The test duration was 320 seconds. The sampling step was 0.25 seconds.

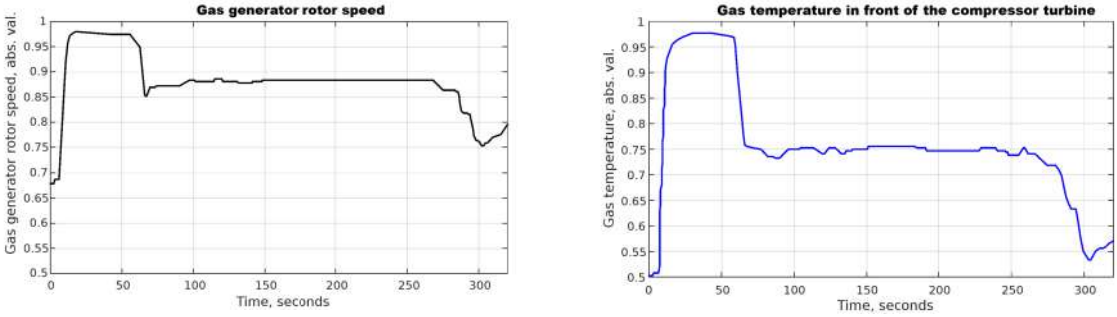
The n_{TC} and T_G^i data obtained during the Mi-8MTV helicopter's flight tests using the onboard monitoring system were preliminarily cleared of noise interference and abnormal emissions. After that, they were transformed into time series are the parameter's sequences ordered by time [43]. To ensure the time series with different scales comparability, the z-normalization procedure was applied:

$$z\left(n_{TC}\right)_i=\frac{n_{TC}^{(i)}-\frac{1}{N}\cdot\sum_{i=1}^{N}n_{TC}^{(i)}}{\sqrt{\frac{1}{N}\cdot\sum_{i=1}^{N}\left(n_{TC}^{(i)}-\sum_{i=1}^{N}n_{TC}^{(i)}\right)^2}},\ z\left(T_G^{¿}\right)_i=\frac{T_G^{¿(i)}-\frac{1}{N}\cdot\sum_{i=1}^{N}T_G^{¿(i)}}{\sqrt{\frac{1}{N}\cdot\sum_{i=1}^{N}\left(T_G^{¿(i)}-\sum_{i=1}^{N}T_G^{¿(i)}\right)^2}},\quad(80)$$

where $N = 1280$.

Thus, the parameters n_{TC} and $T_G^{¿}$ resulting dynamic diagrams after data normalization have the form shown in Figure 8.

The n_{TC} and $T_G^{¿}$ normalized values formed the training dataset, which fragment is presented in Table 2. It is noted that the dataset is homogeneous according to the Fisher-Pearson [44, 45] and Fisher-Snedecor [46, 47] criteria (the homogeneity assessment results are presented in Table 3).



a b

Figure 8: Dynamic diagrams of the TV3-117 engine's gas generator rotor speed (a) and gas temperature in front of the compressor turbine (b)

Table 2
Training dataset fragment

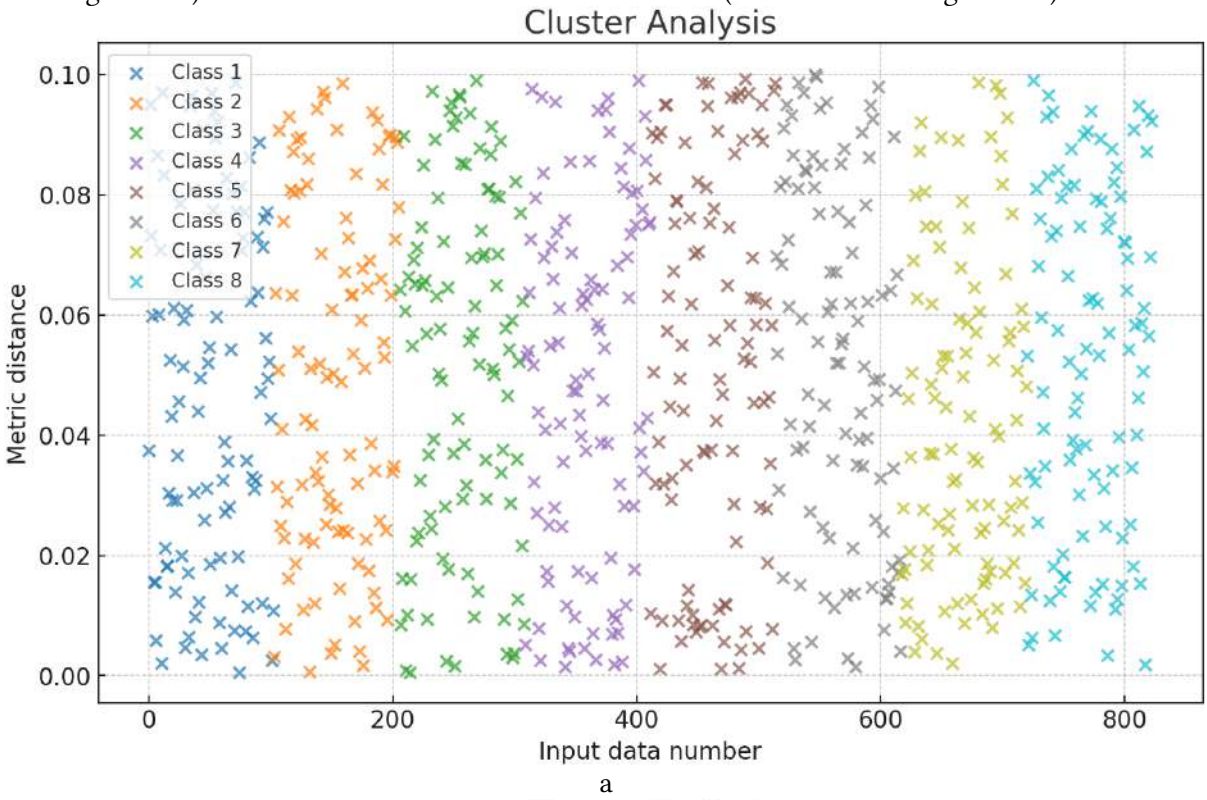
Number	n_{TC} parameter	$T_G^{¿}$ parameter
1	0.985	0.983
...	...	...
256	0.983	0.981
...	...	...
512	0.977	0.975
...	...	...
768	0.981	0.983
...	...	...
1024	0.982	0.987
...	...	...
1280	0.986	0.989

Table 3
Results of the training dataset homogeneity assessing according to the Fisher-Pearson and Fisher-Snedecor criterions

Parameter	The χ^2 calculated value / The $\chi^2(\alpha, 1)$ critical value	The F_{ij} calculated value / The $F_{critical}(\alpha = 0.01, 1279)$ critical value	Decision on the training dataset homogeneity
n_{TC}	6.418 / 6.6	1.122 /1.139	The dataset is homogeneity.
$T_G^{¿}$	6.476 / 6.6	1.128 /1.139	

To check the training dataset (Table 2) representativeness, the cluster analysis method (k-means [48]) was used. The training and test datasets were formed by random division. The proportion was 2:1, which is 67 and 33 % (858 and 422 elements, respectively). The training dataset's (Table 2)

clustering revealed 8 groups (classes I...VIII). This indicates the eight clusters identification. This observation confirms the training and test datasets (Figure 9) structure's similarity. Based on these results, the optimal dataset sizes for the n_{TC} and $T_G^{\dot{c}}$ parameters values were established. The training dataset consisted of 1280 elements (100 %). The control dataset consisted of 858 elements (67% of the training dataset). The test dataset consisted of 422 elements (33% of the training dataset).



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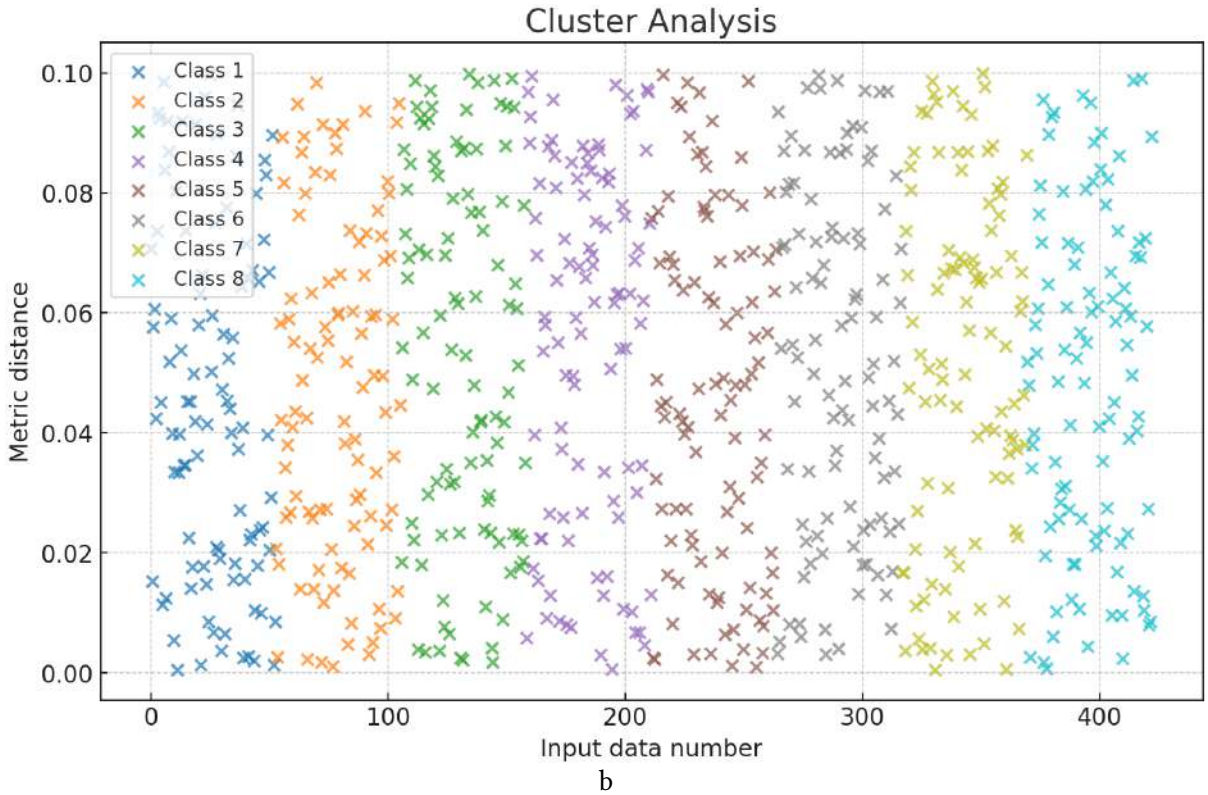

b

Figure 9: The parameters n_{TC} and $T_G^{\dot{c}}$ values cluster analysis results: (a) training dataset (858 elements); (b) test dataset (433 elements)

The proposed fully connected neural network (see Figure 2), consisting of two hidden layers with 16 and 8 neurons, respectively, was trained using the Keras library [49]. The "time_delay" factor was

separately allocated for the predict, and the original dataset was divided into training and test datasets, where the test dataset constituted 33 % of the total amount. SmoothReLU [35] was chosen as the activation function for the hidden layers, and the mean square error (MSE) [35] was used as the optimization criterion. The model was optimized using the Adam algorithm with the training step parameter set as 10^i, where i varies from 1 to 4. Each configuration was trained for 10 epochs, after which the most successful one was selected based on the loss function and predict accuracy indicators, which was then further trained for 100 epochs. The best results were demonstrated by the model configured with the Adam optimizer (training rate 0.0001) and two hidden layers containing 460 and 230 neurons, with SmoothReLU activation [35].

Figures 10 and 11 show the neural network's accuracy and loss diagrams. The obtained diagrams prove the neural network's convergence on 100 training epochs, since both the accuracy and loss on the training and test datasets coincide on the 100th training epoch. In this case, the accuracy reaches 0.99537 (99.537 %), and the loss decreases to 0.00511 (0.511 %). It is noted that after the 100th training epoch, the neural network's occurs overtraining effect. The neural network's overfitting effect, observed after 100 training epochs, is that the model begins to adjust too precisely to the training dataset, including its noise and random deviations, instead of identifying general patterns, which result the data on the training dataset continues to demonstrate high accuracy and low loss, and on the test (validation) set, a deterioration in performance is observed, since the model loses the ability to generalize to new data, having begun to "remember" the training dataset's specific features, which reduces its practical applicability.

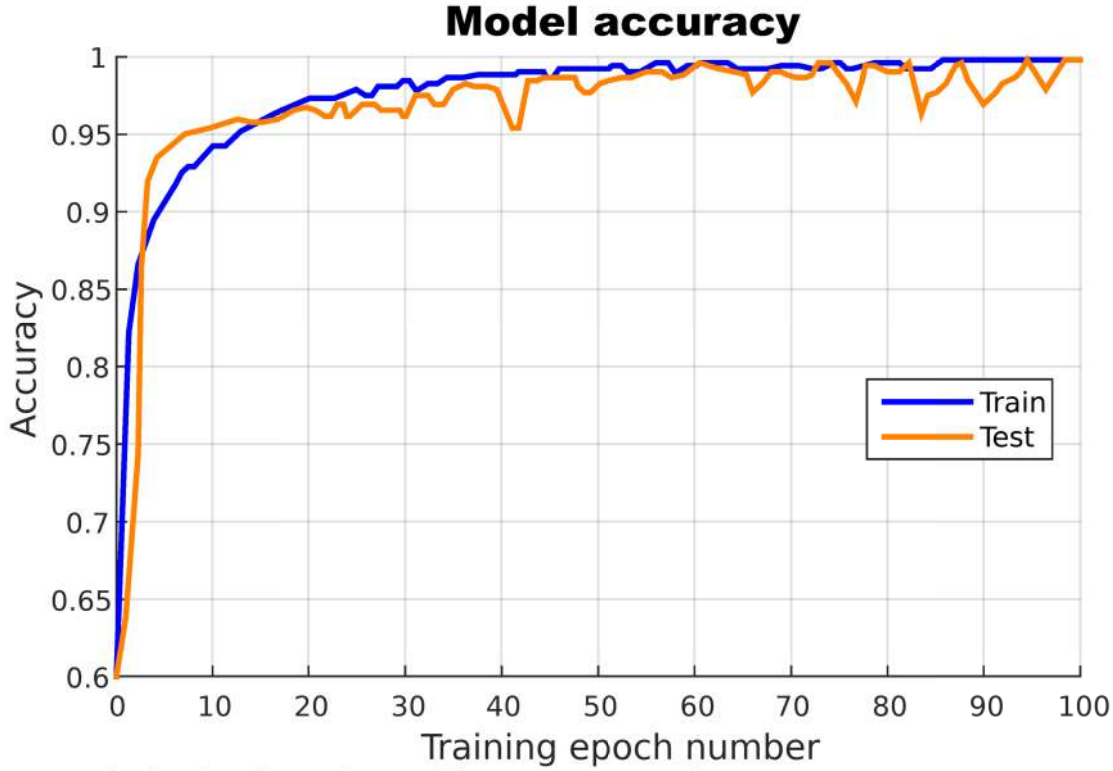

Figure 10: The developed neural network's accuracy metric diagram

Thus, it was found that further training leads to the neural network's generalization abilities deterioration. To prevent this effect, early stopping [50, 51] and regularization $\lambda \cdot \sum_{l=1}^{L} \left(W^{(l)}\right)_2^2$ in (33) were applied.

The developed neural network's predictive assessment ability was carried out on a test dataset, where Figure 12 shows a diagram demonstrating the delay value's predicted results correspondence to the actual data.

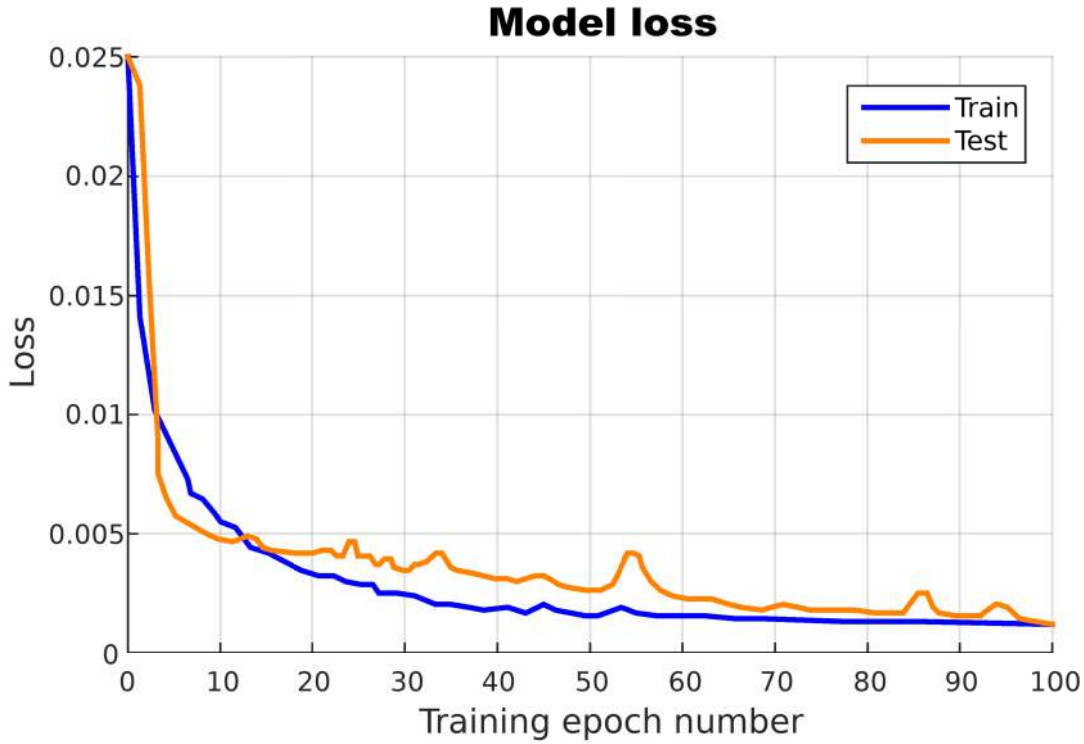

Figure 11: The developed neural network's loss function diagram

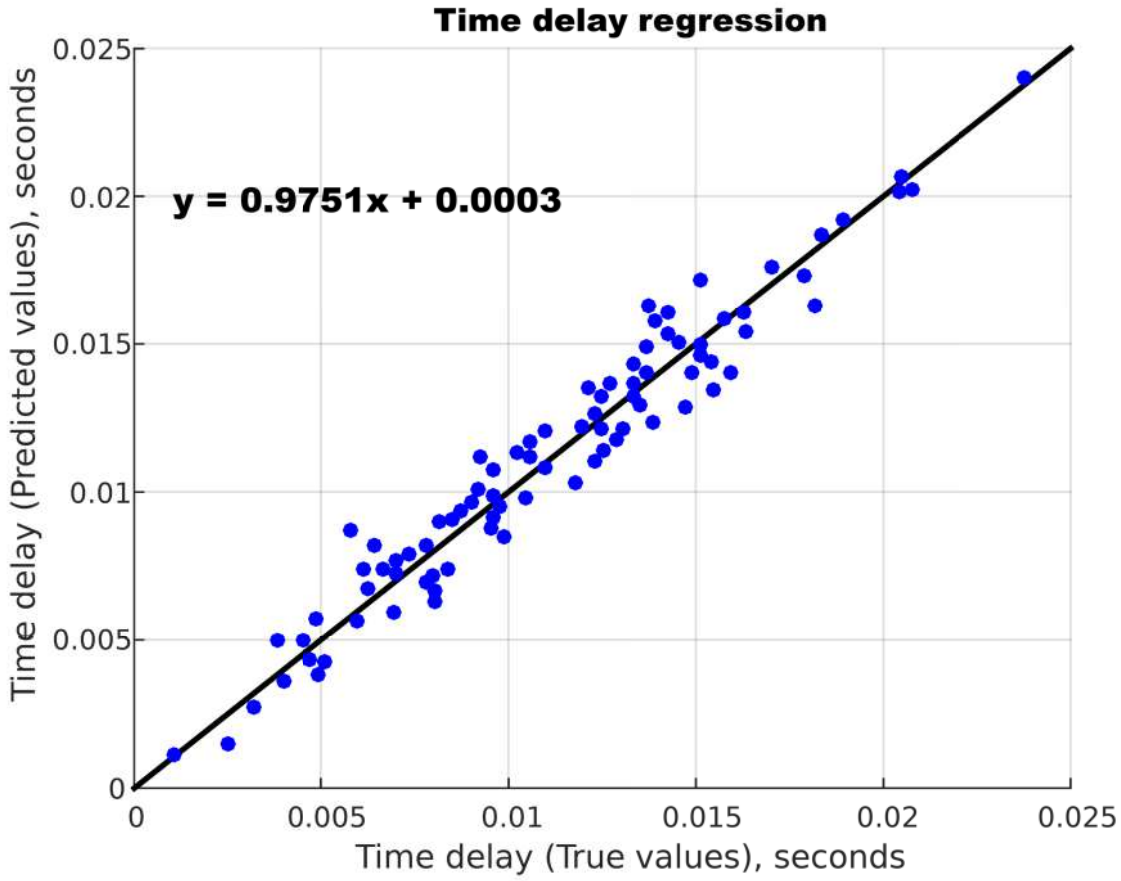

Figure 12: Diagram of predicted delay values vs. reference values

The predict errors distribution's analysis was also conducted, presented in Figure 13. It follows from the diagram that the developed model demonstrates high accuracy in determining delays in the gas temperature control channel based on the factor's given set, without an error's obvious bias in any direction.

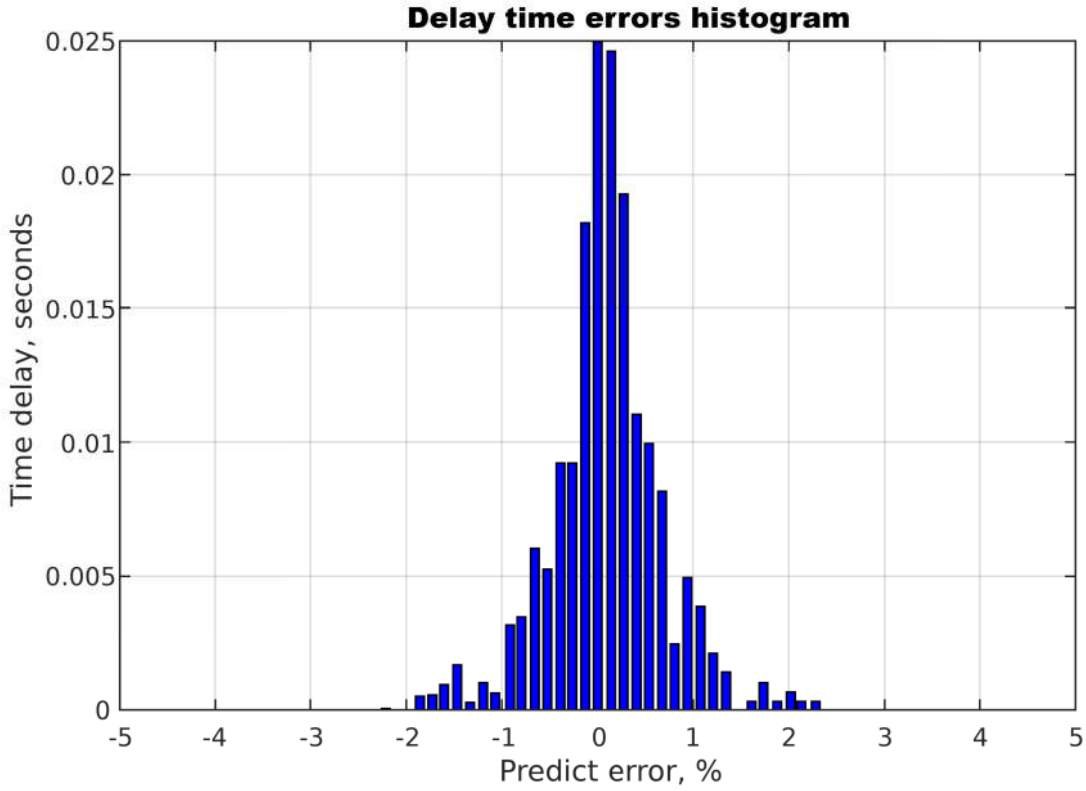

Figure 13: The predicted delay value's deviations distribution histogram

To assess the predicted delay values with the observed data correspondence, the determination coefficient and its adjusted version were calculated [52]. The obtained results R^2 = 0.9717 and adjusted R^2 = 0.9720 indicate a significant degree of relations between the neural network's predicts and the reference data.

To improve the predicted value's accuracy, a confidence interval construction technique is used, which aim is to take into account uncertainties arising from errors in data collection, errors in reference values, or random noise generated by a neural network with a reliability given level. Since there is no strictly mathematically sound algorithm for determining such intervals for neural networks, a quantile approach is proposed: the interval boundaries for the 95% reliability level [53] are set based on the quantiles of 0.025 and 0.975, which leads to the interval [−1.162; 1.077], covering forecast errors in 95% of the model cases (Figure 14).

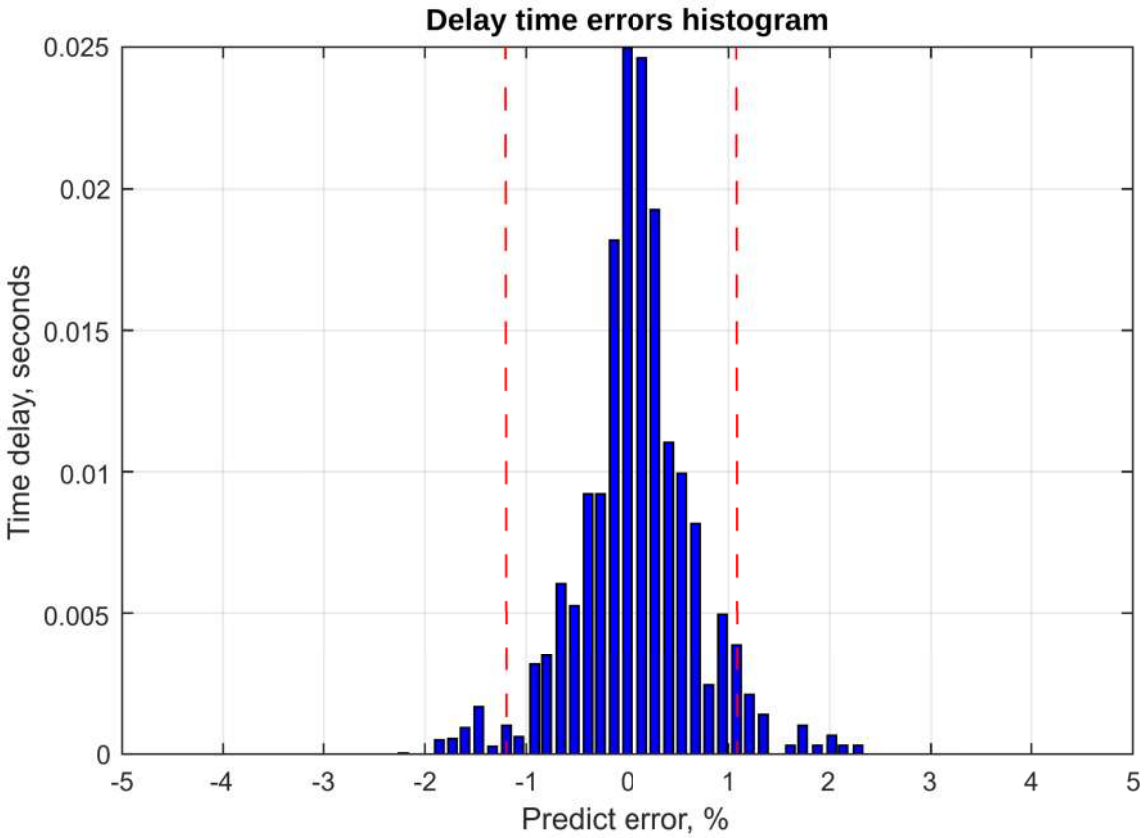

Figure 14: The predicted delay value's deviations distribution histogram with 95% interval of predicted value's deviations

Considering that 95 % of the neural network errors fall within this interval, we can conclude that for any predicted value of τ the following confidence interval is valid: $[\tau - 1.162; \tau + 1.077]$.

Figure 15 shows the dependence of the delay values on the frequency in the range from 1.9 to 2.1 Hz, with special attention paid to the 1.96 Hz point, where pronounced oscillations are recorded, which may indicate the system's resonance effects or specific dynamic features. The neural network use in this context has a positive effect on reducing the delay, since it is able to model complex nonlinear relations between system parameters and accurately predict optimal control modes, which ensures the control signal's timely correction. Due to the neural network's adaptability, it is possible to achieve a faster system response (the delay values using the neural network did not exceed 0.016 seconds, which is 36 % higher compared to the case without using a neural network), the operation stabilization in critical frequency ranges and, as a result, a significant reduction in delay.

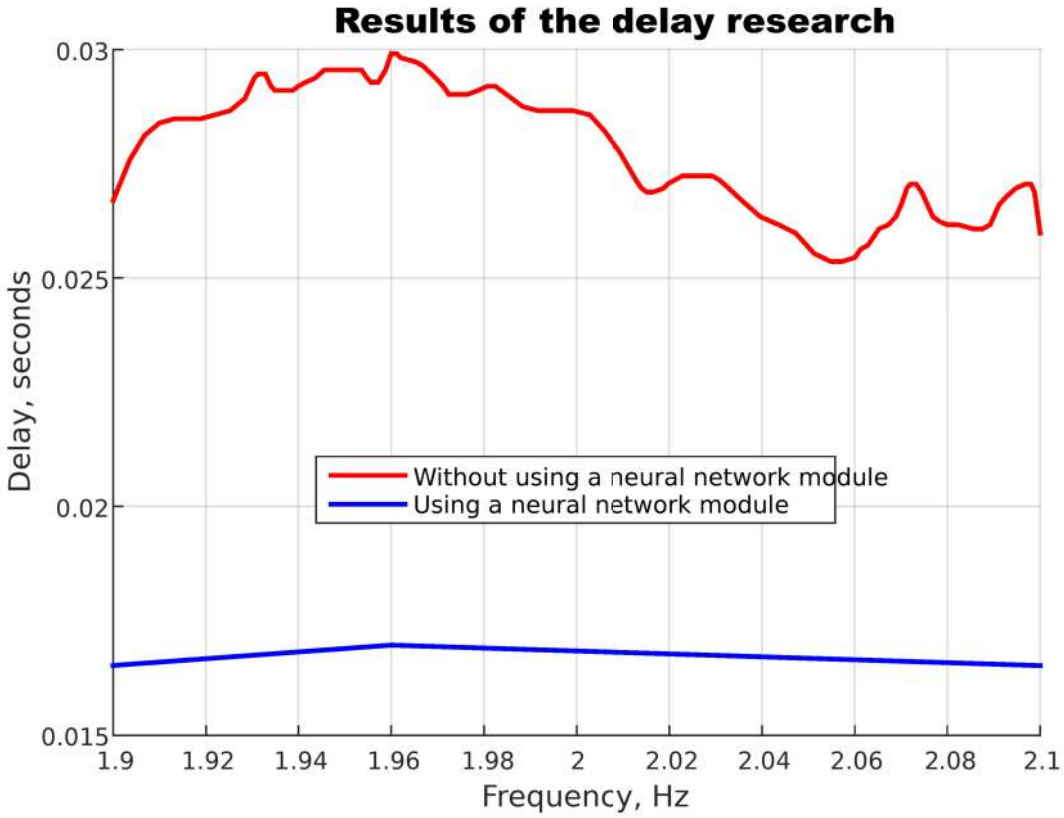

Figure 15: Diagram of the delay value's dynamics in the resonant frequency vicinity

6. Discussion

In this research, the helicopter TE's intelligent gas temperature controller (see Figure 1) was developed based on a double summation scheme, which allows for the measuring sensors inertial delays compensation and transient processes optimization in real time. Its special feature is the integration of adaptive algorithms with a differentiator and a neural network module, providing dynamic correction of control parameters and high control accuracy (up to 99.5 %).

A method has been developed based on a mathematical model of delayed dynamics (1) and determination of the control error (2), where the state is predicted using Taylor series expansion (6). The intelligent control law (8), supplemented by the coefficient's adaptive correction using the gradient descent scheme (9), allows real-time optimization of control parameters and compensation for inertial delays.

A neural network module for delay estimation correction (see Figure 2) has been developed, which is implemented using a deep fully connected neural network, which architecture is specified by (28)–(32), where the final delay estimation is determined according to (32). The module's special feature is the nonlinear activation functions use in hidden layers for accurate approximation of the relations between input features and delay correction, which ensures the system's dynamic adaptation in real time.

The neural network module's testing results demonstrate high training accuracy: the accuracy and loss function diagrams (Figures 10 and 11) confirm the model's convergence on the training and test datasets, and the predicted and reference delay value's correspondence diagram (Figure 12) indicates small predicting errors, which is further confirmed by the errors distribution on the histogram (Figure 13). In addition, the delay value's dynamics analysis in the resonant frequency vicinity (Figure 15) shows a 36 % reduction in delay, which indicates a significant improvement in the system's adaptive capabilities.

However, despite the positive dynamics and results achieved, the research has some limitations:

1. The modeling and testing results were obtained on the experimental data limited set basis (Figures 7 and 8), which may reduce the methodology applicability in conditions other than the test dataset.

2. The neural network module's overtraining effect is observed (Figures 10 and 11), which limits its ability to generalize and may negatively affect the delay prediction in real operating conditions.
3. The approximate compensation methods use, such as Taylor series expansion (6) and transfer function's simplification, may not provide sufficient accuracy of compensation for inertial delays during sudden changes in operating modes (Figure 15).

Future research could be structured as follows (Table 4).

Table 4
The future research roadmap

Number	Research direction	Action
1	Expansion of the experimental base and testing conditions	1. Conducting additional tests in various operating modes and extreme conditions to increase the data representativeness [54]. 2. Integrating data from various helicopter platforms and the experimental dataset's long-term collection to the specific conditions influence reduce [55].
2	The neural network module's stability and generalizing ability	1. The regularization method's design and implementation, ensemble models, and advanced architectures (e.g., RNNs or transformers) to prevent overfitting [56]. 2. Application of adaptive early stopping and cross-validation algorithms to improve of latency prediction's reliability [57].
3	Refining mathematical models for compensating inertial delays	1. The approximate methods extension (e.g., using more complex expansions or alternative dynamic models) to improve compensation accuracy, especially with sudden changes in operating modes [58]. 2. The adaptive self-tuning algorithms integration that allows the transfer function parameter's dynamic adjustment in real time [59].

The research demonstrates that the innovative adaptive control methods development requires technological improvements while simultaneously complying with regulatory and ethical standards when applying it on board a helicopter, taking into account the rights and responsibilities of human operators [60].

7. Conclusions

The helicopter TE's intelligent temperature controller has been developed that uses a double summation scheme with an adaptive observer and correction links, which provides effective compensation for the measuring sensor's inertial delays.

The neural network module's implementation for delay estimation correction allows the control parameter's dynamic adaptation in real time, which is a significant improvement compared to traditional approaches.

Simulation showed a reduction in overshoot from 8.0 to 1.5 % and a reduction in the transient process time from 4.2 to 3.3 seconds, and the neural network module's testing demonstrated a forecasting accuracy of 99.537 % (losses is 0.511 %) with a determination coefficient of R^2 = 0.9717 and a reduction in delay to 0.016 seconds (an improvement of 36 %).

In the future, authors are going to explore the experimental base and testing conditions expansion, including additional tests in various operating modes [61] and the data integration [62] from various helicopter platforms to reduce the specific conditions influence. They also plan to develop robust neural network modules using regularization methods [62], ensemble models [63], and adaptive algorithms [64], as well as refine the mathematical models for compensating for inertial delays by integrating adaptive self-tuning algorithms [65, 66] in real time.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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Intelligent Landmine Detection with Unmanned Aerial Vehicle Mounted Thermal Camera

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Abstract

This work is devoted to the development of landmine detection intelligent system with the usage of unmanned aerial vehicle mounted thermal camera. The problem is considered under the framework of object detection. The proposed framework is based on the robust pre-processing pipeline, with a lightweight neural network performing feature extraction, classification and bounding box detection tasks. Pre-processing pipeline includes normalization, texture extraction, and noise reduction algorithms to minimize the impact of defects in the images on the accuracy of the neural network. The neural network was trained on a custom-collected dataset of various landmines with a low-altitude flyby, with captured images being used to train the neural network. The proposed method shows perfect recall (1.0), adequate precision (0.909), high Rand index (0.98), and intersection over union(0.963) metrics.

Keywords

Object detection, landmine detection, thermal imagery, convolutional neural network

1. Introduction

Even though the usage of landmines were greatly reduced by Ottawa treaty, landmine pollution is still an acute problem around the world. It is estimated that over 60 countries are still contaminated by various types of landmines and unexploded ordnance, according to the 2023 Landmine Monitor report. Most common hazards are landmines, improvised explosive devices, and artillery shells that did not explode on impact, collectively referred to as explosive ordnance (EO). It is estimated that over 4700 civilians were killed or injured in 2022 by explosive ordnance, according to the Landmine Monitor report.

Ukraine is one of the most heavily landmine-polluted countries in the world, with various estimates stating that up to a third of its territory is polluted by EO. Removal of EO is paramount for the restoration of economic activity, which can only be achieved via the process of landmine removal. The process of landmine removal is tedious, high risk, and is complicated by high rate of false positives due to various debris, present on the minefields. As such, having a detailed map of the minefield with the most likely areas where explosive ordnance is present is extremely useful for engineers that will be performing the landmine removal operation. Drones, in particular unmanned aerial vehicles (UAVs) are particularly useful, as they are able to perform a safe and fast scan of the area.

However, the process of collecting images is not the only problem, as covering 1 square kilometer at a useful resolution requires approximately 60,000 images. An expert takes, on average, 3 minutes to verify the image for presence of EO, or 3000 man hours to process 1 square kilometer. In the context of all landmine contaminated territory of Ukraine, it is estimated that over 500 million man hours are required to manually process the images. Artificial intelligence, specifically computer vision algorithms, can greatly speed up the process and make it possible to create detailed maps of landmine polluted area for the following landmine removal operation.

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2. Literature review

2.1. .Remote Sensing for Landmine Detection

Modern mine detection methods are based on the use of a combination of sensors and mobile platforms to quickly collect information about a mined area. The most common types of sensors used for mine detection are ground penetrating radar, electromagnetic sensors, hyperspectral cameras and infrared cameras. Most of these sensors have a number of disadvantages that limit the possibility of their use with unmanned aerial vehicles - weight, price, the requirement to be directly close to the ground (which can lead to detonation of the explosive device), however, the development of infrared camera technologies has made it possible to create lightweight, compact and relatively inexpensive sensors that can be used in combination with artificial intelligence to detect mines. Infrared cameras are used to detect shallowly buried metal mines as well as non-metallic mines [1].

The presence of a buried mine is determined based on the difference in thermal characteristics between the buried objects and the surrounding soil, since a buried mine affects the thermal conductivity within the soil, resulting in a temperature difference between the buried object and the soil. [2]. This temperature contrast is measured using a thermographic camera that detects radiation in the infrared region of the electromagnetic spectrum and appears as pseudocolor in thermal images [3].

However, detecting mines in thermal images is difficult due to the temporal behavior of soil temperature distribution during the day and night, as well as the presence of other buried objects [4].

Given the difficulty of object detection in thermal imaging images, there is a need to develop suitable image processing-based decision tools for accurate landmine detection. Various researchers have proposed various methods to improve the detection of buried mines in thermal infrared images. Infrared thermal imaging can work with passive (natural) or active (man-made) heat sources. However, they are influenced by weather conditions and soil moisture [5]. Since the thermal differences between bare soil and the soil surface above buried mines are quite small, a circular symmetrical spatial filter is applied to enhance these differences [6].

Visibility of buried targets using an infrared and charge camera has been found to be difficult during sunrise and sunset [7]. Ederra proposed mathematical morphological tools for denoising and segmentation of individual images [8]. Since the raw thermography sensor image is unlikely to provide satisfactory information due to interference from solar radiation, soil conditions, humidity, etc., the complex steps of infrared thermography processing, including data acquisition, data preprocessing, anomaly detection, and evaluation of the thermal and geometric properties of the detected anomalies, are explained using appropriate techniques [9]. Image processing techniques such as Karhunen-Loeve transform (KLT), Kittler and Young transform have been used to reduce the data size and computation time in thermal image based mine detection systems [10]. KLT and watershed segmentation were proposed for landmine detection applications [11]. The concept of spectral differentiation and detection algorithm, based on the principles of pattern recognition, were developed [12]. The dynamic behavior of the scene due to time variation and cooling of solar illumination during landmine detection and its impact on the images are analyzed using image processing tools [13]. A 3D finite difference thermal model was presented and validated for detecting landmines in outdoor minefield datasets [11].

2.2. .Artificial Intelligence for Landmine Detection

The operating principle of IR radiation is based on the fact that different objects can have different thermal characteristics [12], i.e. thermal conductivity and heat capacity. Mines can be thought of as an unnatural volume for heat flow within the soil. This may cause a specific spatiotemporal thermal pattern on the soil surface, which can be detected using IR imaging systems [13]. According to [14], IR-based detection systems mainly depend on the condition of the soil surface, the nature of the soil, climatic changes, the characteristics of buried objects, their position and finally the thermal excitation. When all these factors are handled properly, IR thermography is a noteworthy detection tool for locating buried objects.

If these space-time thermal patterns are due to mines, it is called a volumetric effect. On the other hand, if they occur due to disturbed soil, it is called surface effect [15]. We have experienced that the surface effect can only be detected for a short period of time after planting. During this period, the thermal contrast is quite visible [20]. An IR system can detect these anomalies as evidence of mines [16].

According [2], IR images do not require too much pre-processing and this system can work with passive (natural) or active (man-made) heat sources. However, it can be affected by weather conditions and soil moisture. Soil moisture has a positive effect on the thermal signature of a non-metallic mine and increases the detection speed; on the other hand, it reduces the detection rate of metal mines due to the shift of thermal characteristics with humidity [17].

Deeply buried objects cannot be detected using IR sensors [18]. The maximum detection limit for mines using IR radiation is about 10 cm [19]. [15] visualizes buried landmines under three different soil surface conditions. According to their conclusion, mines buried at moderate depths in the soil do not create a direct signature.

Similar studies have been published on mine detection using IR sensors. In [20], authors monitored areas containing buried anti-tank mines and analyzed changes in surface temperature over a diurnal cycle to compare different soil textures and soil moisture. According to their analysis, it is possible to predict the cyclical behavior of the thermal signatures of mines, with the exception of soil with silty loam. Authors of [21] used 24-hour time series of IR images in their studies. They used the Karhunen-Love transform (KLT) to reduce the data size and applied three different methods to segment the mines. They enhanced the image/images using gray scale morphology. The watershed marker algorithm is then applied to the data for segmentation using these three methods. In [22] authors have presented landmine detection using KLT and watershed segmentation. In their research, they propose a series of night images from 20:00 to 01:00 with a time interval of 30 minutes. According to them, images taken in the morning and afternoon contain redundant information.

Therefore, they used a series of night images and KLT, which reduces the number of images and therefore the time required to process the data.Authors of [23] worked on a 3D thermal model for mine detection problems. In [24] a 3D thermal model to study the effects of mines on bare soil is presented. They worked with mines with low or no metal content. They simulated the thermal behavior of soil with known boundary conditions. After this, they proposed an iterative method for data classification. This iterative method gives the nature and depth of the objects. In [25], a thermal radiometric model is presented. They used the finite element method to describe thermal phenomena. They used a 25cm anti-tank mine stimulator and a virtual sensor believed to be an LWIR camera operating at a wavelength of around 10μm. Additionally, they incorporated surface roughness into their thermal and radiometric models to account for surface self-shading due to soil surface topology. According to the authors, the surface temperature above the mine is lower at dawn, and the surface is hotter during the day. Finally, at night, the soil layer above the mine is colder. Additionally, they introduce the concept of spectral differentiation and developed a detection algorithm based on pattern recognition principles in another study [26]. They used a weighted difference between visible and IR images from the same scene to remove reflected radiation from the warm atmosphere to reduce interference caused by reflected light. According to the authors, there is a trade-off between reducing interference and increasing the mine signature [27]

In [28], authors investigated how a thin outer metal casing and an air gap left over buried anti-personnel and anti-tank mines affected IR images. They used the finite element method (FEM) to describe thermal phenomena. They modeled buried anti-tank mines with and without a thin metal outer casing, as well as surface/buried anti-personnel mines. To analyze the effect of the top air gap, they also simulated an anti-personnel mine with a top air gap. The simulated mines had the thermal properties of TNT in the model. According to their results, the thin metal outer shell has a significant impact on the temperature distribution due to the noticeable difference in thermal conductivity between the metal shell and TNT.

The upper air gap has a more noticeable effect on the temperature change in depth over a given time cycle due to the low thermal conductivity of the air gap compared to the soil. In addition to this, their results show that surface mines create greater temperature extremes than buried mines.

Thanh et al. [28] presented and validated a 3D thermal model for mine detection in open minefield datasets. They proposed a finite-difference approximation of generalized solutions of the model. In addition, they proposed methods to evaluate the thermal properties of bare soil and the air-soil interface. They validated their estimated soil parameters by comparing simulations with real

data sets. They [29] also developed a method that gives the thermal diffusivity, depth and size of buried objects. In the first stage, they presented a method that can detect landmines. This method depends on thermal differences at the soil surface caused by buried objects. In the second part, their proposed method finds the thermal diffusivity, depth and size of buried objects using an inverse problem formulation. 3D modeling was developed to simulate the passive IR signature of landmines that are buried or placed on the soil surface using (FEM). In [30], a two-step method is proposed in a review study. In the first step, they found the soil temperature using their new thermal model provided by the thermal properties of the soil and the buried object. At the second stage, the discovered objects are classified using the proposed improved inverse problem setting. They called the second step setting up an inverse problem to detect landmines. They evaluate the depth, shape of a buried object, and its thermal diffusivity using their two-step method. In [31], authors have proposed a method that can reproduce the thermal properties of outdoor conditions with reduced data size and compressed time. They generated a generalized formula for this purpose. They imaged the embedded test area for eight and six hours over a two-hour period. They used a binary reduction algorithm to detect mines.

3. Problem statement

In this work, the mine detection task will be considered as an object detection problem - in target thermal images it is necessary to generate a bounding box of pixels that correspond to mines and other objects of interest (EOs). More formally, thermal image I treated as a matrix of size $H \times W$, where H is the matrix's height, W is the matrix's width. Each element of the matrix x represents an image pixel and contains a single rational value $x \in R$, which corresponds to the "brightness" of the surface in a given pixel (the higher the temperature, the higher the brightness). The work solves the problem of constructing an object detection function that turns the input thermal image I into the list of detected objects $I' = [(((x_{1l}, y_{1l}), (x_{1r}, y_{1r})), y_1), ..., (((x_{nl}, y_{nl}), (x_{nr}, y_{nr})), y_n)]$,where each element $((x_{nl}, y_{nl}), (x_{nr}, y_{nr}))$ is a bounding box of target object and, $y \in C, C = \{1, 2, 3 \ldots, c\}$, is the class of the detected object.

To avoid the effect of the "curse of dimensionality", H and W should be limited in size. When collecting information using a drone, there are two possible projections of data - individual frames obtained by the drone and an orthomosaic (stitched frames). To limit W and H in this paper, individual frames collected by an unmanned aerial vehicle (UAV) are used. If an orthomosaic is available, it must be divided into small (depending on the configuration of the neural network) patches for further processing.

When assessing the effectiveness of the proposed solution, it is important to choose the right metrics, since it is important not only to correctly classify the mine, but also to avoid type I errors (false negatives).

The following metrics will be used in this work:

1. Precision (Mine / No Mine) – the ratio of all true results to the total number of true and false true results: $Precision = \frac{TP}{TP + FP}$;
2. Recall (Mine / No Mine) – the ratio of all true results to the total number of true and false negative results. When detecting mines, it is extremely important to avoid Type I errors, which makes recall one of the key metrics: $Recall = \frac{TP}{TP + FN}$
3. Rand index, also known as classifier accuracy. This metric evaluates the ratio of true positive and true negative predictions to all predictions: $Rand = \frac{TP + TN}{TP + TN + FP + FN}$
4. Intersection over union (IoU) is a metric that is used to measure the accuracy of bounding box predictions: $IoU = \frac{[A \cap B]}{[A \cup B]}$

When assessing the quality of the intelligent system, UN standards for humanitarian demining will be used. The UN landmine clearance standard for detection rate is 99.6% for humanitarian demining.

4. Method

The work proposes an integrated approach to information collection, data preprocessing, feature extraction, and classification. The approach is based on using a quadcopter to fly over a mined area, with further image processing using a neural network. The general scheme of the approach is presented in Fig 1.

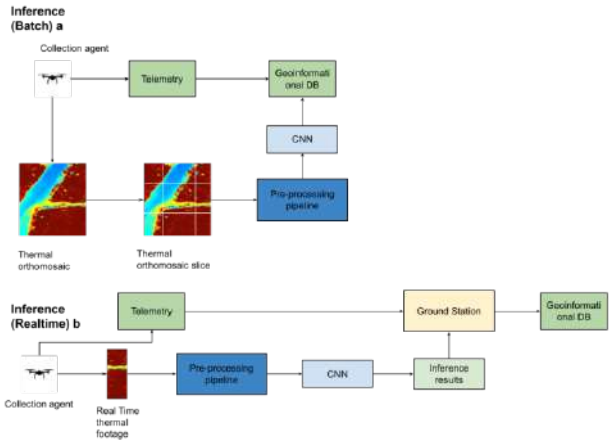

Figure 1: The proposed method's framework

4.1. . Data Collection

A quadcopter, or other type of a UAV, with a thermal camera mounted perpendicular to the ground, is used to perform a flyby over the landmine contaminated area. The flight is performed at an altitude of 10-15 meters above ground level, with a predetermined route. The height is selected depending on the area of the landmine-polluted area and weather conditions. The flyby is carried out in the afternoon, preferably in low clouds, which provides better thermal contrast between the mine and the ground.

4.2. . Data Preprocessing

The data obtained after the flight goes through a preprocessing pipeline to prepare for feature extraction and subsequent classification. The general processing pipeline is shown in Fig. 2.

The first stage of processing is normalization. When normalizing, it is important to take into account the nature of the data. Since all images collected during one flight must have the same distribution to improve generalization, normalization occurs in two stages. The first step uses linear normalization to improve the contrast of all images and bring them to the same distribution:

$$I_N = (I - Min)\frac{(newMax - newMin)}{Max - Min} + newMin\,, \quad (1)$$

where *Min* is the minimum brightness value in the original image, *Max* is the maximum brightness value in the original image, *newMax* is the new maximum value in the image, *newMin* is the new minimum value in the image.

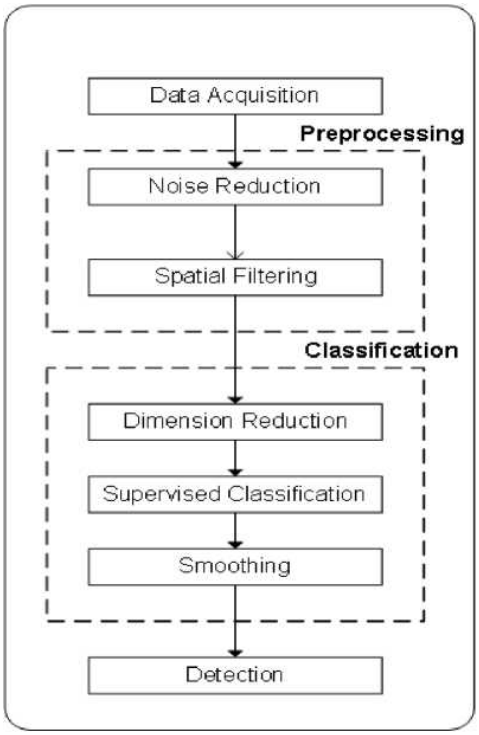

Figure 2: Data processing pipeline

Linear normalization uses classical parameters *newMax* = 255, *newMin* = 0. At the same time *Max* And *Min* the parameters are selected as the maximum and minimum values for the entire span, and not in each image separately.

After linear global normalization, local normalization is performed to increase the contrast of regions that may be unevenly illuminated by the sun. To do this, local contrast stretching is used, which is equivalent to a convolution operation using an averaging kernel:

$$I_n(x,y)=\frac{newMax*(I(x,y)-\min_I(x,y))}{\max_I(x,y)-\min_I(x,y)}, \quad (2)$$

Where *newMax* is a maximum value after normalization, $I_{x,y}$ is the pixel value *x,y* in the original image, *min(x,y)* is the minimum value for the convolution kernel in pixel x,y, *max(x,y)* is the maximum value for the convolution kernel in pixel x,y.

For local gradient stretching, it is recommended to use a convolution kernel with padding, which allows for a maintainance the original image size. Parameter values are set depending on the resolution of the input image.

After normalizing the image and stretching the gradient, the result is a high-contrast image, but it will contain noise. Stones, debris, grass, and immitators will create noise in the image, leading to a high rate of false positives. From a demining perspective, this is not a critical issue as they can be safely inspected manually, but it does add significant labor and time to demining operations. To overcome this limitation, filtering removes speckle noise and weak signals that complicate further image processing.

Filtering consists of two stages – de-texturization and morphological filtering.

Using the local binary pattern (LBP) histogram method. This is a spatial filtering method that is used to extract spatial features, especially textures, which significantly increases classification accuracy. LBP adjusts the intensity value of each pixel using a mapping function to a neighborhood function. Initially, the neighborhood function is selected. Moore's neighborhood function is often used, but other neighborhood functions can be used to increase the floorI perceive texture. For each pixel, a vector of texture characteristics is calculated:

$$LBP_p=\sum_{p=0}^{p-1} s(g_p-g_c)2^p, s(x)=\begin{cases}1 \, if \, x\geq 0\\ 0 \, otherwise\end{cases}, \quad (3)$$

where g_p is the pixel's neighbourhood value, *P* is the selected neighbourhood type, g_c is the central pixel of the nighborhood *P*.

Once the image is converted to LBP encoding, they are used to construct a texture histogram. The biggest advantage of LBP is its high processing speed and ability to store spatial patterns for high-resolution mine detection.

After the histogram is created, an additional filtering step is performed. This step uses morphological filtering to remove noise and spots that form the image. Morphological filtering filter removes noise and insignificant objects from the texture. Morphological image processing is a set of tools for analyzing and processing structural features of images based on set theory. These techniques can extract and enhance the spatial characteristics of objects in images, making them extremely useful in image processing and computer vision.

The first stage is erosion - reducing the number of objects in the image by removing pixels at the boundaries of objects. This removes minor noise:

$$(A \ominus B)(i,j) = \min_{x,y \in B} A(i+x, j+y), \tag{4}$$

where A is the original image, B is a structural element. After this, the image must be restored to avoid loss of features, for which the expansion operator is used:

$$(A \; S \quad B)(i,j) = \min_{x,y \in B} A(i-x, j-y), \tag{5}$$

where A is the original image, B is a structural element. The morphological filtering operation is a composition of the erosion and dilation operator, which removes noise from the image and makes it clearer.

These steps ensure that the input images are cleaned, noise is removed and textures are preserved (if possible). These steps also partially extract features (through LBP and morphological filtering), which allows for a more simple neural network architecture, decreasing the number of learnt parameters.

4.3. . Feature Extraction and Classification

This paper considers a hybrid architecture for the task of segmentation and classification. Due to the need to calibrate the sensitivity of the mine detection network, two-step segmentation is used, which allows the sensitivity and accuracy of the network to be adjusted separately from each other.

Segmentation will be performed in two stages - the first stage uses U-net with residual connections to identify areas of interest that are most likely to contain a mine. These zones are marked, expanded and fed into a convolutional neural network to classify the type of mine.

Convolutional neural networks are used to solve the problem of feature extraction and classification. This is a common approach for solving computer vision problems. There are many architectures, but most of them are designed to process complex images with a large number of features and possible classes. After pre-processing, the dimensionality and complexity of the data is significantly reduced, which makes it possible to synthesize [32, 33] a simpler architecture [34].

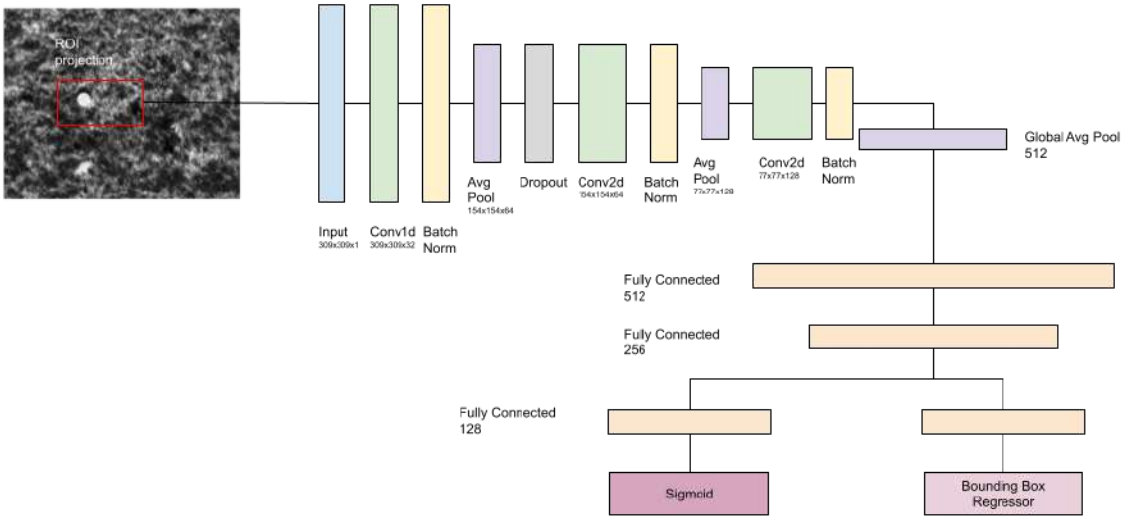

Figure 3: Proposed neural network architecture

The proposed network consists of the following types of layers:
1. Convolutional layer is the primary building block of CNN where the convolution operation occurs. Filters (kernels) slide over the entire image, calculating the dot product between the filter and part of the input image, creating feature maps;
2. The pooling layer performs dimensionality reduction of feature maps, preserving the most important features. The most common types are MaxPooling (selects the maximum value in each window) and AveragePooling (selects the average value);
3. BatchNorm layer is used to normalize feature maps, which increases stability and learning speed;
4. The exclusion layer is used to prevent overfitting by randomly "turning off" some neurons during training;
5. A fully connected layer has its neurons connected to all the neurons of the previous layer, which enables combining features, making a final classification decision;
A key feature of the proposed architecture is the relatively low depth of the convolutional network. This allows you to reduce the number of parameters, which speeds up training and processing. This was achieved through the use of a comprehensive preprocessing pipeline.
For object detection, region-based convolutional neural networks were selected as a baseline for the model. Specifically, we use fast R-CNN with a convolutional pathway outlined above. While this is not the most robust algorithms, it performs reasonably well due to the nature of the domain and robust pre-processing pipeline, which partially extracts the features, reducing the learning capacity that is expected of neural network.
To achieve object detection, ROI projection is used to extract areas of the image that are then passed through the convolution path outlined above. Global average pooling is used to build a feature vector from the image, passing through two fully connected layers. After this, a pathway branches into two – the classification pathway which utilizes sigmoid to perform binary classification task and through a bounding box regressor, which extracts the bounding box from the feature vector of the image. The selected architecture is somewhat simplistic, however it was considered to have sufficient learning capacity in the context of this problem [38].
To train the learner, a multi-task loss is used. Classification loss is based on a simple binary cross-entropy loss. Bounding box repressor needs a location-aware loss, as such, a modification of IoU is used as a loss function. The problem with using IoU itself is that if no overlap is detected between the target object and the classified image, the loss function becomes constant. To overcome this, a variety of modifications of IoU is designed to serve as a loss function. In this paper, a generalized intersection over union (GIoU) is used. The rectangle bounding box C is used to build a convex of an object that encloses both A and B:

$$GIoU = \frac{[A \cap B]}{[A \cup B]} - \frac{C \setminus (A \cup B)}{C}, \tag{6}$$

where A and B are groundtruth and predicted bounding box areas, C is the bounding box that covers both A and B.
The GIoU loss is constructed as following:

$$L_{GIoU} = 1 - GIoU. \tag{7}$$

To handle object detection, a selective search, ROI polling, and bounding box prediction modules are added to the network's architecture.

5. Experiment & Result

To test and evaluate the proposed system, an experiment was conducted to collect data, train and evaluate the proposed system. Data was collected using a DJI ZH20T thermal camera attached to a Mavic Phantom T4 quad copter. The mines were installed on the surface and also buried in the ground to a shallow depth (up to 10 cm). The study used two types of mines - anti-tank and anti-personnel, both types had a metal casing. The flight was carried out at a low altitude (5-6 meters) and medium altitude(10-11 meters). The integrity of the grass cover was damaged only in the places where the mines were installed, but otherwise the cover remained intact. Data were collected in clear, warm weather to minimize noise and maximize image quality. The temperature was shifting thought the day, which ensured high quality thermal gradient in the collected dataset.
A limited amount of debris and uneven ground was present in the collection area, which also created additional noise and false-positive spots in the thermal gradient on the ground. This creates additional challenge for the neural network, as this noise is not fully removed by the pre-processing

pipeline. Collected data set consists of 436 thermal images, with 62 images being removed due to low quality.

After data collection, the resulting frames undergo pre-processing, eliminating low-quality frames. Low-quality footage refers to footage with high levels of noise or blur. Such frames have an extremely negative impact on the quality of classification and detection of objects, reducing the accuracy of the neural network. One of the main problems is motion blur. If the desired object falls into a blurred area of the image, this significantly increases the bounding box of the desired object, negatively affecting the training of the network, so in this study such frames were removed from the original data set. In further research, it is possible to use an algorithm to restore the quality of images. An example of a blurry (low-quality image) is shown in Fig. 4

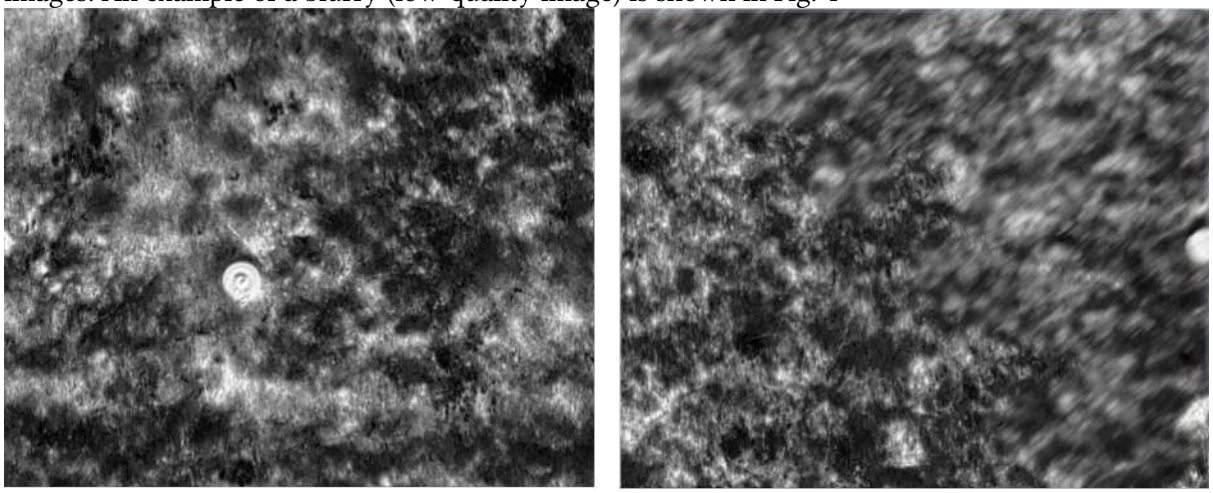

Figure 4: Normal(a) and blurred image (b) examples from the dataset. Motion blur is one of the major contributing factors.

The neural network was trained in batches of 16 images. The sample size is bolstered by applying "weak" augmentations that consist of rotations, stretching, and other augmentations from RandAugment. The preprocessing stage was performed for each batch separately to increase the generalization ability of the neural network. Adam learning algorithm with a decaying learning rate from 0.001 to 0.00001 during the training of the neural network. Default parameters were used during the initial training, with further fine-tuning during the experiment using methods outlined in [35, 36]

The results of the training are presented in the table 1, and a sample of classification is given in Fig. 5

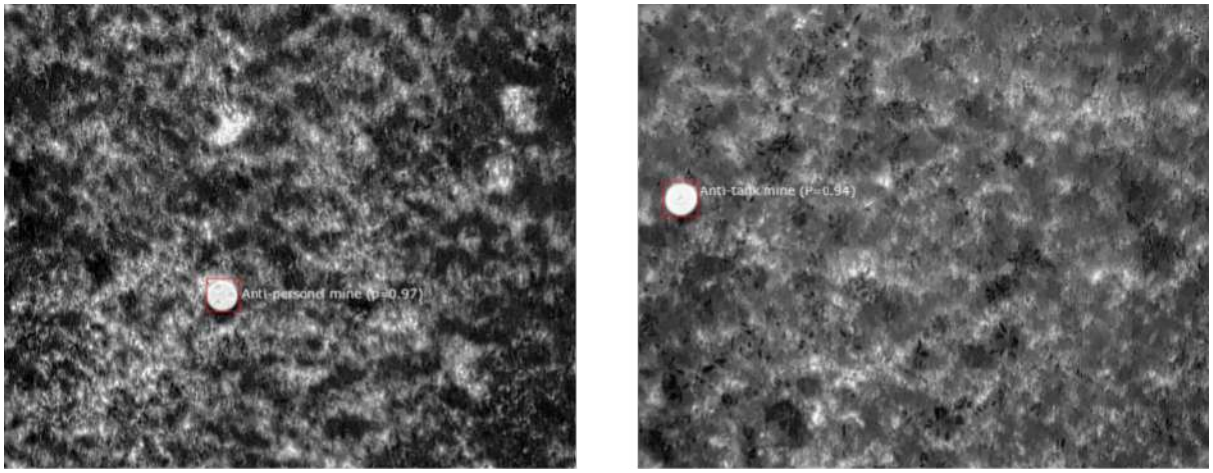

Figure 5: Object detection result. The system is unable to classify the type of the landmine, labels were added manually for clarity

Table 1
Experiment result

Metric	Value	Note
Precision	0.909	Precision is reasonably high, with several samples being mislabeled (with weak blur / noise)
Recall	1.0	All landmines were successfully detected
Rand index (OA)	0.98	Overall high, apart from few misclassifications
IoU	0.963	Bounding boxes around the mines are precise, apart from few cases where they are somewhat larger than anticipated.

Overall, the algorithm performs well, detecting both landmines installed over the ground and under the ground, with high reliability, however it should be noted that even on a small number of samples and with a large number of training iterations, the network has modest precision. While in the case of landmine detection this is not as bad as having low recall, it is still something that should be addressed, as a high number of false-positives leads to slower and more costly landmine removal operation.

Conclusion

This paper presents a comprehensive framework for landmine detection with thermal imagery cameras installed on a mobile platform (UAV). The proposed approach is based on the combination of deterministic pre-processing to pre-extract features from the images, followed by a region-based convolution neural network detector for feature extraction, classification and ROI extraction.

The proposed approach was able to achieve high recall (1.0) and moderate precision (0.92). Algorithm's average IoU is reasonably high at 0.875, with results being skewed by false positives and unclear edge for buried landmines.

Future research will be focused on addressing some of the shortcomings of the algorithm discovered in this paper. First such shortcoming is the diversity of the dataset. The research is based on the dataset collected over 1 flyby over a limited area, with limited number of landmines available and in new-perfect weather conditions. Future dataset collection should be focused around building a more challenging and diverse dataset for neural network training and evaluation. The second consideration to address is identifying optimal architecture for the neural network itself. In this research, a simple yet robust fast CNN-based region object detection. It works reasonably well, considering the nature of data and feature pre-extraction step, however exploration of other options, such as mask-based CNN could improve performance of the method. Lastly, in this paper binary object detection was used. For the proposed method to be practically valuable, it would also be beneficial to identify the type of the landmine, so future research will focus on multi-class object detection to not just detect the mine itself, but also it's type or exact model.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Intelligent monitoring system for analyzing vehicle drivers state based on adaptive deep learning models

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Abstract

This paper focuses on the development of an intelligent driver monitoring system based on adaptive deep learning models to enhance road safety. The research explores advanced deep learning techniques, particularly convolutional neural networks and their modifications, such as ResNet50 and MobileNetV2. Special attention is given to the stages of data preprocessing, augmentation, training and testing dataset formation, as well as model training and fine-tuning. A conceptual framework and architecture for an intelligent driver monitoring system have been developed, incorporating two modules based on different deep learning models. An experimental study was conducted to compare the performance of various convolutional neural network (CNN) architectures, including classical CNN, ResNet50, MobileNetV2, EfficientNetB0, and VGG16, in detecting driver fatigue and drowsiness. Signs of overfitting were identified in the ResNet50 and MobileNetV2 models when applied to the selected datasets, highlighting the need for further hyperparameter optimization. The developed testing scripts enable real-time analysis of behavioral indicators of drowsiness and driver distraction. The proposed system is designed for non-invasive and high-precision real-time monitoring of driver conditions, including fatigue, drowsiness, and distraction detection. The findings confirm the effectiveness of adaptive deep learning models for driver state monitoring. The developed system demonstrates the capability to detect signs of fatigue, drowsiness, and distraction, which may help reduce the likelihood of road accidents. Experimental results indicate that the choice of an optimal neural network architecture depends on the specific task requirements and the available computational resources.

Keywords

deep learning, data analysis, intelligent monitoring systems, vehicle drivers state

1. Introduction

The advancement of modern technologies and the increasing computational power make intelligent big data analysis systems essential tools for automating complex processes and making well-founded decisions [1]. The application of intelligent technologies and methods enables the identification of intricate patterns, resource optimization, and enhanced prediction accuracy across various scientific and industrial domains [2]. The growing volume of data necessitates efficient algorithms for processing, interpreting, and utilizing information in real time, emphasizing the significance of developing advanced analytical models. Intelligent data analysis systems contribute to the autonomy and adaptability of technological solutions, ensuring their reliability, efficiency, and security [3].

So, in the modern context, road traffic safety is becoming an increasingly pressing issue, necessitating the implementation of innovative methodologies and technological solutions aimed at minimizing the likelihood of traffic accidents and enhancing driver protection. A crucial aspect of this issue is the physiological and psychological state of the driver, including their level of concentration, degree of fatigue, emotional stability, and ability to respond promptly to changes in road conditions. Consequently, the study and development of highly effective driver state monitoring algorithms have become priority areas in the field of transportation safety.

Traditional driver monitoring approaches based on physiological parameters such as heart rate and galvanic skin response have significant limitations. Their implementation in real-world operational conditions is associated with technical challenges, the need for specialized equipment, and potential discomfort for the driver. In this context, non-invasive monitoring based on video

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stream analysis presents a compelling alternative. This approach enables the assessment of driver states by examining visual indicators, including facial expressions, head position, blink frequency and patterns, as well as other markers of fatigue and decreased attention [4].

With advancements in artificial intelligence (AI) and data-driven analysis, the accuracy and reliability of automatic driver state detection have significantly improved. A key role in this progress is played by machine learning (ML) and deep learning (DL) techniques, particularly deep neural networks (DNN), which have demonstrated outstanding performance in computer vision and behavioral pattern recognition. DL enables models to autonomously extract meaningful features from large datasets, eliminating the need for manual feature engineering. State-of-the-art architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers, ensure efficient real-time video stream processing, allowing for accurate and timely detection of potentially hazardous driver states [1,3,5].

Thus, the development of driver state assessment approaches based on video analysis using DL techniques represents a promising direction in transportation safety. Intelligent monitoring systems built upon these technologies can promptly respond to changes in driver conditions, mitigating the risk of accidents. Their integration into modern vehicles has the potential to significantly enhance overall road traffic safety.

2. Description of Problem in Literature Review

According to the analysis of a number of literary sources and the opinion of authoritative authors, in practice there are various methods for determining the driver's condition, the most priority and promising of which are based on: wearable sensors, processing the driver's visual conditions and the acoustic environment.

2.1. Methods based on processing biometric information and classic hardware sensors

One of the first and main areas of focus for many researchers and organizations, including automobile companies, is the development of sensors for collecting biometric information. Biometric information about a driver allows us to understand his condition and ability to drive a vehicle. Biometric information includes information such as electrocardiogram, electrodermal activity, blood pressure levels and visceral fat levels, as well as exercise levels, sleep patterns and diet. An important factor is also the correct interpretation of all the above parameters [6].

For a example, the authors of paper [7] conduct a study demonstrating the significant effectiveness of electroencephalography data in monitoring driver states, particularly in detecting drowsiness and loss of attention. To achieve this, they developed a system comprising an EEG recording device, a computational unit capable of signal processing and classification, and a real-time feedback mechanism that alerts the driver and wakes them up by emitting an audio signal. Drawing upon the analysis of the authors' perspectives existing classical methods of measuring heart rate limit or interfere with driver performance. In addition to the completeness and accuracy of measurements, it is very important that the driver monitoring system does not limit or interfere with the driver's performance [8]. Therefore, traditional methods are not suitable for measuring heart rate in a vehicle, and a non-wearable monitoring system is desirable, although the reliability of the data obtained is inferior to that of wearable systems. Such driver monitoring systems should be able to correctly determine the driver's state of readiness without limiting his or her movement [9].

It is worth noting that driver state monitoring using MEMS (Micro-Electro-Mechanical Systems) sensors represents an innovative approach to enhancing road safety. MEMS sensors are characterized by their small size, high sensitivity, and precision, making them ideal for integration into driver monitoring systems. According to [10-12], MEMS continuously collect data on the driver's physiological parameters and movements. The gathered information is processed using machine learning algorithms to detect anomalies or patterns indicative of potential danger. For instance, the system can identify patterns associated with drowsiness or driver distraction. If a potential risk is detected, the system can issue auditory or visual alerts, as well as haptic warnings via seat or steering wheel vibrations. Some advanced systems may also implement active safety measures, such as engaging autopilot functions or initiating an automatic vehicle stop if the driver

fails to respond to warnings [13]. A key aspect of all the reviewed scientific studies is the complexity of their technical reproducibility due to the necessity of multiple integrations and the non-trivial process of configuring operational modes of technical devices, combined with the consideration of individual characteristics and predispositions of specific drivers. However, collectively, the results obtained by the authors indicate the promising potential of MEMS sensors for driver state monitoring.

2.2. Methods based on processing the driver's visual state

Modern DNN generally outperform traditional methods in accuracy and automation. However, they require large datasets, have limited interpretability, and demand high computational resources [14, 15]. These challenges drive the development of hybrid models that combine the strengths of traditional approaches with deep learning techniques. The increasing prevalence of in-vehicle information systems significantly impacts road safety, as their use contributes to visual, manual, and cognitive driver distraction, potentially impairing driving performance. Additionally, drivers frequently engage in secondary activities such as eating, drinking, adjusting the radio, and using mobile devices. These distractions reduce their focus on the road and increase cognitive load, thereby heightening the risk of traffic accidents. One effective method for detecting driver distraction involves analyzing facial orientation and gaze direction. Most modern driver monitoring systems follow a multi-step approach [16]:

1. Face recognition and head tracking – initially, a face detection algorithm is applied, and its results serve as input for a more precise head-tracking system.
2. Facial landmark localization – this step involves identifying key facial features such as the eyes, enabling anthropometric analysis of both the face and head.

One of the most widely used face recognition algorithms is the Viola-Jones method, which has inspired several enhanced versions, such as PICO [17]. This approach refines the standard Viola-Jones object detection framework by employing a cascade of binary classifiers to scan images at multiple scales, achieving high processing speed while maintaining accuracy.

Furthermore, head position in three-dimensional space can be assessed by analyzing its tilt relative to the camera. This evaluation allows for the estimation of head rotation angles, tilt levels, and deviations, providing insights into the driver's gaze direction. Advanced facial analysis methods also incorporate more sophisticated algorithms capable of generating a 3D model of the head and face using a single camera. One of the most well-known systems in this category is based on 49 tracked 2D facial landmarks utilizing the supervised descent method (SDM). In this context, it is also important to note that many modern approaches incorporate tree-based models, Deformable Part Models (DPM), SDM, explicit shape regression, and local binary feature extraction techniques [18]. However, these methods often suffer from performance limitations when exposed to varying lighting conditions. Uneven light sources, asymmetric shadowing on the face and eye region, and abrupt changes in illumination—caused by factors such as shadows from buildings, bridges, and trees—pose significant challenges for accurate facial feature detection. Consequently, further research is required to adapt these algorithms for real-world driving conditions, enhancing the reliability and precision of driver monitoring systems.

2.3. Methods based on the acoustic environment

Previously, one of the primary challenges in studying and developing voice analysis algorithms was the limited availability of training datasets. However, with the advent of voice assistants, researchers and developers have gained access to an almost unlimited variety of speech data from diverse speakers, significantly enhancing the potential for speech analysis.

Acoustic characteristics of speech can be classified according to auditory-perceptual prosodic concepts, including prosody (pitch, intensity, rhythm, pauses, and speech rate), articulation (clarity of speech), and voice quality (e.g., breathy, tense, harsh, hoarse, or modal voice). Modern approaches to speech emotion recognition rely on precise temporal modeling of acoustic feature contours, known as feature level dynamics (FLD). This method results in the extraction of hundreds or even thousands of features used for classification. The process follows a four-step framework [19]:

- The speech signal is segmented into small time frames and smoothed using windowing functions such as the Hamming window.
- Signal processing is performed, including speaker recognition and feature extraction for each individual frame.
- The values of each frame-level feature are aggregated into FLD contours.
- The one-dimensional temporal sequence is projected onto a scalar feature that captures the temporal dynamics of the acoustic contour.

A key advantage of this sequential approach is its enhanced ability to model the contribution of both smaller units (words) and larger segments (phrases) to the prosodic structure of an utterance [20].

2.4. Focus and goal of work

Current methods for assessing driver states based on sensor data and acoustic environment analysis have several limitations that reduce their effectiveness in real-world applications. Physiological sensor-based technologies (e.g., heart rate monitoring or galvanic skin response) face challenges related to invasiveness, complex calibration requirements, and high sensitivity to individual physiological variations. Furthermore, these systems require continuous physical contact with the driver, which can cause discomfort and limit usability. Acoustic analysis-based approaches also exhibit constraints, such as susceptibility to high background noise levels within the vehicle cabin, variations in individual speech patterns, and the need for complex signal processing to achieve high detection accuracy.
Additionally, these methods are less effective when the driver remains silent or exhibits minimal speech activity.

Given these limitations, hybrid approaches that combine computer vision with biometric data analysis present a promising direction for improving driver state monitoring. Specifically, integrating face recognition, head and body posture assessment, and MEMS sensor data enables the development of more robust monitoring systems. Video-based analysis offers a non-invasive means of evaluating driver behavior, while MEMS sensors provide physiological and behavioral insights, enhancing the accuracy of fatigue, drowsiness, and distraction detection.

Thus, the aim of this paper is to develop intelligent monitoring system for analyzing vehicle drivers state based on adaptive deep learning models.

3. System's concept development

3.1. Main functions formalization

To address the outlined problem, the following concept of intelligent monitoring system for analyzing vehicle drivers state on can be proposed:

- Development system's first module (M1) with a DNNs, adapted from existing DL models, for detecting key points on the face and head with the purpose of binary or multiclass classification, aimed at assessing the driver's level of fatigue.
- Development system's second module (M2), also adapted from existing DL models, for detecting distractions affecting the driver during driving.
- Aggregation of the outputs from M1 and M2 to enhance result accuracy and reduce the number of false positives.

To comprehensively assess the condition of a vehicle driver for drowsiness detection through automated recognition and classification of video stream images, followed by an analysis of the driver's focus level or distraction from the traffic process, it is proposed to develop and use two separate modules that implement different DL models, which have models to handle the processing and analysis of data for assessing driver drowsiness: by analyzing head posture considering distractions and by analyzing eye condition. A generalized scheme of the project stages is presented in Figure 1.

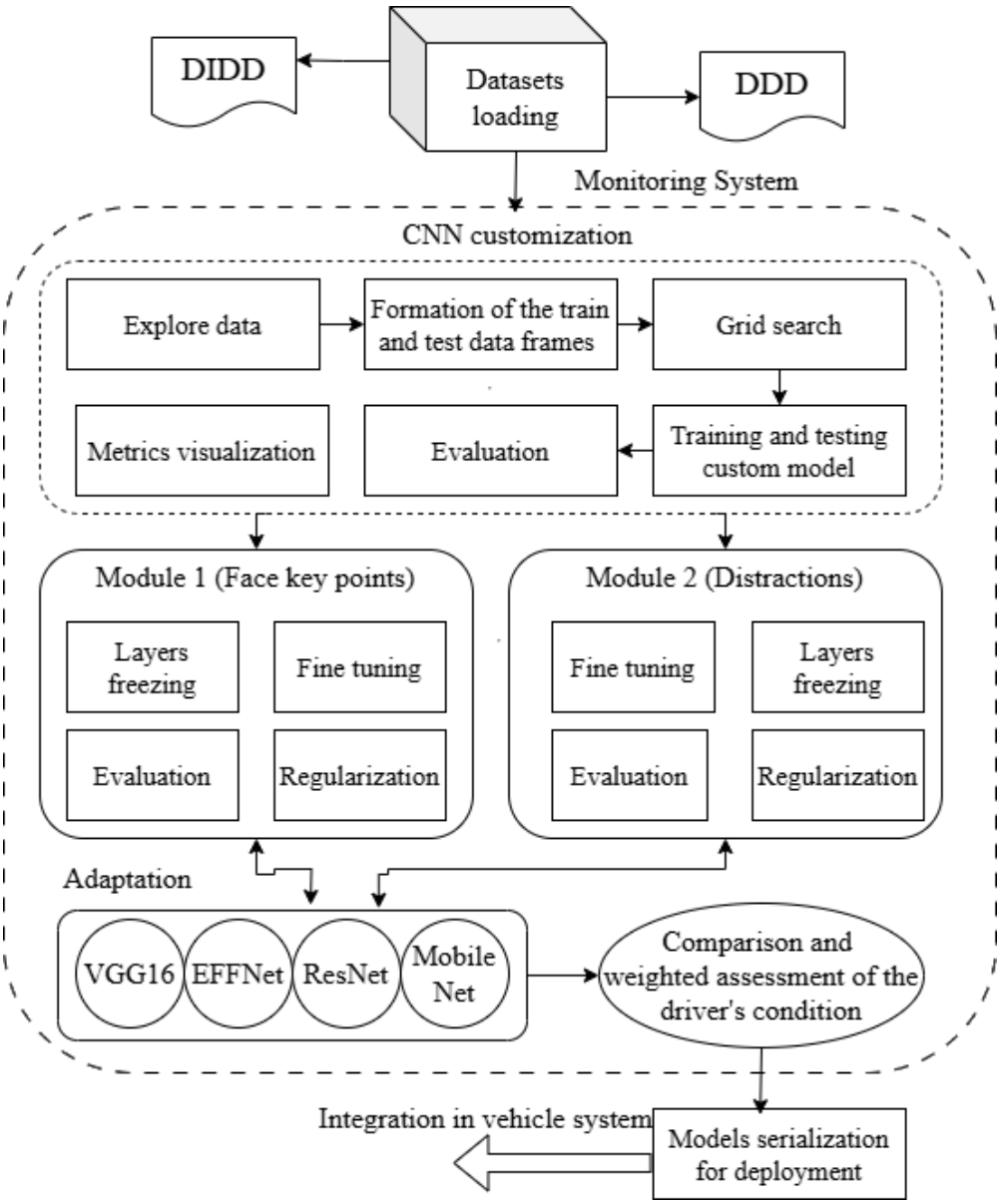

Figure 1: Intelligent system consept stages scheme

The key aspects of the implementation are as follows:

- Data selection and loading. At this stage, a dataset containing images and data regarding the driver's condition (head posture, eye condition) is chosen and loaded into the working environment. For deep learning models like ResNet and MobileNet, high-resolution video frames are loaded, as both models have been pre-trained on large image datasets.
- Data preparation and preprocessing. This step involves standardizing the input format, including resizing images, normalizing pixel values, and augmenting the data. For ResNet and MobileNet, images are resized to a fixed format (e.g., 224×224), and augmentation techniques such as rotation, mirroring, and brightness adjustment are applied.
- Forming training and testing subsets. Based on the size of the data, the dataset is split into training and testing subsets in an 80/20 or 70/30 ratio. Cross-validation is used to enhance the robustness of the models.
- Creating and loading DL models. Pre-trained DL architectures, such as ResNet-50, can be used, with the last fully connected layer being replaced for driver condition classification tasks. The MobileNet model can also be used for lightweight and fast classification, followed by fine-tuning and adding fully connected layers to process specific data.
- Training and fine-tuning models. The training process includes adjusting hyperparameters such as learning rate (0.001-0.01), number of epochs (10-30), and optimization functions (such as Adam or SGD).

- Metrics evaluation and results analysis. At this stage, the models' quality is assessed using appropriate metrics to analyze the driver's condition based on the selected factors.
- Decision making. Based on the data and predictions, decisions are made to adjust system actions accordingly.

In the implementation of the described concept, the adaptive feature fusion mechanism is of key importance, which includes the following stages:

- weighted fusion of features based on the dynamic confidence coefficient of the model;
- Bayesian aggregation of probabilistic predictions to improve the accuracy of determining the driver's state (analysis of the level of drowsiness);
- adaptation of the attention mechanism to focus on the most informative regions of the video stream images;
- optimization of the final assessment of the driver's state using the retrained VGG16 model.

That is, the deployed ResNet, MobileNet and CNN models extract features $F_{cnn} \in \Re^{d_c}, F_{res} \in \Re^{d_r}, F_{mob} \in \Re^{d_m}$ respectively. Then the final representation of the combined features F_{fusion} is defined as:

$$F_{fusion} = w_{res} \cdot F_{res} + w_{mob} \cdot F_{mob} + w_{cnn} \cdot F_{cnn}, \quad (1)$$

where w_{res}, w_{mob}, w_{cnn} – adaptive weights determined through the attention mechanism:

$$w_i = \frac{e^{S_j}}{\sum_j e^{S_j}}, S_j = MLP(F_i), \quad (2)$$

where $MLP(F_i)$ - a multilayer perceptron that learns to predict the importance of each feature channel.

Bayesian aggregation of model predictions is based on probabilistic combination of predictions of each model:

$$P(y|X) = \sum_i w_i P_i(y|X), \quad (3)$$

where $P_i(y|X)$ – the probability of predicting the level of sleepiness produced by each model.

The VGG16 model is used to further validate the output representation by using the following model output correction function:

$$F_{opt} = \sigma(WF_{fusion} + b), \quad (4)$$

where W - learnable transformation matrix, b – bias, σ – activation function (ReLU or softmax).

The final assessment of the driver's condition is calculated as:

$$P_{final}(y|X) = \alpha P(y|X) + (1-\alpha) P_{vgg}(y|X), \quad (5)$$

where α – weighting factor determined based on the confidence level of the VGG16 model.

Given the labor-intensive nature of creating a custom dataset, which includes aggregation, formatting, and labeling, the decision has been made to use existing publicly available datasets compiled by third-party experts for the training and testing of data analysis models.

3.2. Datasets description

In the development of intelligent system's module for processing and analyzing data to assess driver drowsiness based on head position and distraction factors, the driver-inattention-detection-dataset [21] has been selected. This dataset, presented in grayscale, is highly diverse and includes over 14,000 labeled images distributed across six different classes, providing a broad and varied data range for training, validation, and testing tasks specifically tailored for grayscale image processing.

The dataset is organized into three main directories: training (11,942 grayscale images that have been carefully selected and labeled across six classes), validation (1,922 images used for model tuning and performance evaluation during the development process), test (985 images reserved for final verification and comparative analysis of the models). This dataset covers six classes of driver

behavior: dangerous driving, distracted driving, alcohol consumption, safe driving, drowsy driving, yawning.

For further exploration of the potential intelligent system's M2 for a different, more specialized, and pre-processed dataset focusing on driver eye images, besides the previously discussed ResNet50 and MobileNetV2 models, EfficientNetB0 and VGG16 models were selected. The dataset chosen for this purpose is the Driver Drowsiness Dataset (DDD) [22], which contains extracted and cropped images of drivers' faces from video recordings of real-world cases of drowsiness while driving.

This dataset is intended for the development and training of machine learning and deep learning models capable of detecting signs of drowsiness in drivers by analyzing their eye regions.

Since the data were collected from real video recordings, they reflect a variety of lighting conditions, angles, and other factors, making them valuable for creating robust and reliable drowsiness detection systems.

The DDD includes more than 41,790 images of drivers' faces, and the dataset structure is as follows: RGB images with a size of 227×227 pixels, labeled into two classes — "drowsy" and "alert," involving 28 drivers, each assigned a unique identifier.

3.3. Neural network models development

According to M1 logic implementation all the images uploaded into the system are converted to RGB format and resized to 224x224 pixels at the preprocessing stage. The class labels are encoded using one-hot encoding.

For the experiments, it was decided to use a classical convolutional neural network (CNN) architecture, as well as compare it with pre-trained models such as ResNet50 and MobileNetV2.

The ResNet50 architecture includes residual blocks, which help address the vanishing gradient problem common in deep neural networks. Specifically, the model incorporates GlobalAveragePooling2D layers to reduce feature dimensionality, a fully connected Dense layer with 512 neurons and the ReLU activation function, and a final Dense layer with 6 neurons and softmax activation.

The MobileNetV2 architecture employs depthwise separable convolutions, which significantly reduce computational complexity. For driver state analysis, a similar approach to ResNet50 was used, where the base layers of MobileNetV2 were frozen (using pre-trained weights from ImageNet), and GlobalAveragePooling2D layers, a fully connected Dense layer with 512 neurons and the ReLU activation function, as well as the softmax-activated output layer were added.

The training process for both models is similar to that of ResNet50, but MobileNetV2 offers a lower computational load, making it more efficient in environments with limited computational resources.

The CNN model architecture (Figure 2) consists of several Conv2D convolutional layers with ReLU activation, MaxPooling2D subsampling layers, a fully connected Dense layer with 512 neurons, and Dropout to prevent overfitting, along with an output layer with softmax activation for classifying into 6 classes.

```
[15]
model.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: U
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
conv2d_3 (Conv2D)	(None, 24, 24, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 12, 12, 256)	0
flatten (Flatten)	(None, 36864)	0
dense (Dense)	(None, 512)	18,874,880
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 6)	3,078

```
Total params: 19,266,374 (73.50 MB)
Trainable params: 19,266,374 (73.50 MB)
Non-trainable params: 0 (0.00 B)
```

Figure 2: Main CNN model structure

In M2 implementation the research followed the subsequent steps:

- Data preprocessing, including normalization of images and resizing them to the required dimensions for each model (e.g., 224x224 pixels for most models).
- Data augmentation to increase the diversity of the training set and improve the models' robustness (e.g., rotations, shifts, brightness adjustments).
- Model initialization with pre-trained weights, which accelerates the learning process and improves accuracy.
- The ReLU activation function was used as the optimizer, and Sigmoid as the loss function, with binary cross-entropy applied as the loss function due to the binary classification task.
- Testing was performed by splitting the data into training and testing subsets.
- Model performance evaluation, using metrics similar to those in the previous study, and cross-validation to assess the robustness of the models on different data subsets.

4. Experiments and results analysis

In M1 accuracy, F1-score, precision, recall were used as metrics for assessing the accuracy of the models, each of which was evaluated on a test set. Classic CNN is characterized by a simpler architecture, high performance and base accuracy. The ResNet50 model is characterized by higher accuracy due to pre-trained weights, and MobileNetV2 demonstrates moderate (not very high) accuracy, but is more efficient in terms of consumption of computing resources. At the same time, the ResNet50 model copes best with the "SleepyDriving" and "Yawn" classes.

Comparison of F1 Score and Precision metrics evaluation results for adaprive DL models in M1 is shown in Figure 3. It should be noted that there is a consistent decrease in the loss and an increase in accuracy for each model, indicating the absence of overfitting. The ResNet50 model demonstrates the most stable convergence. Visualization of the results of constructing error matrices for adaptive DL models in M1 is shown in Figure 4.

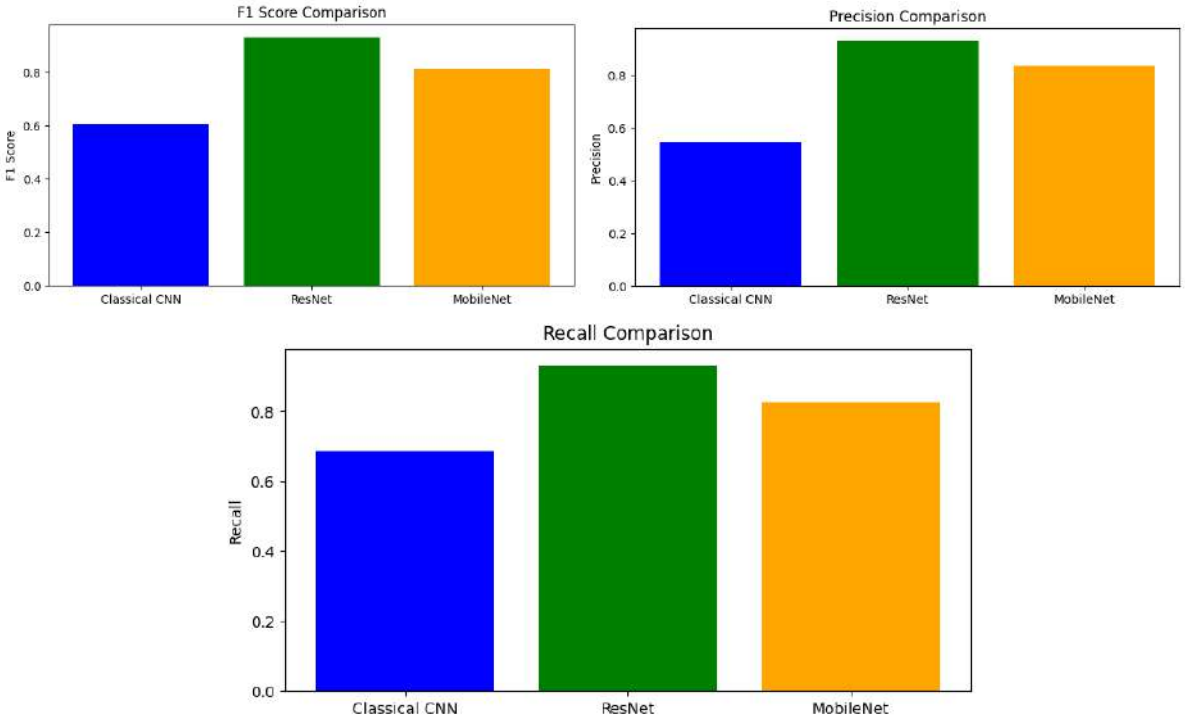

Figure 3: Comparison of F1 Score and Precision metrics evaluation results for adaptive DL models in M1

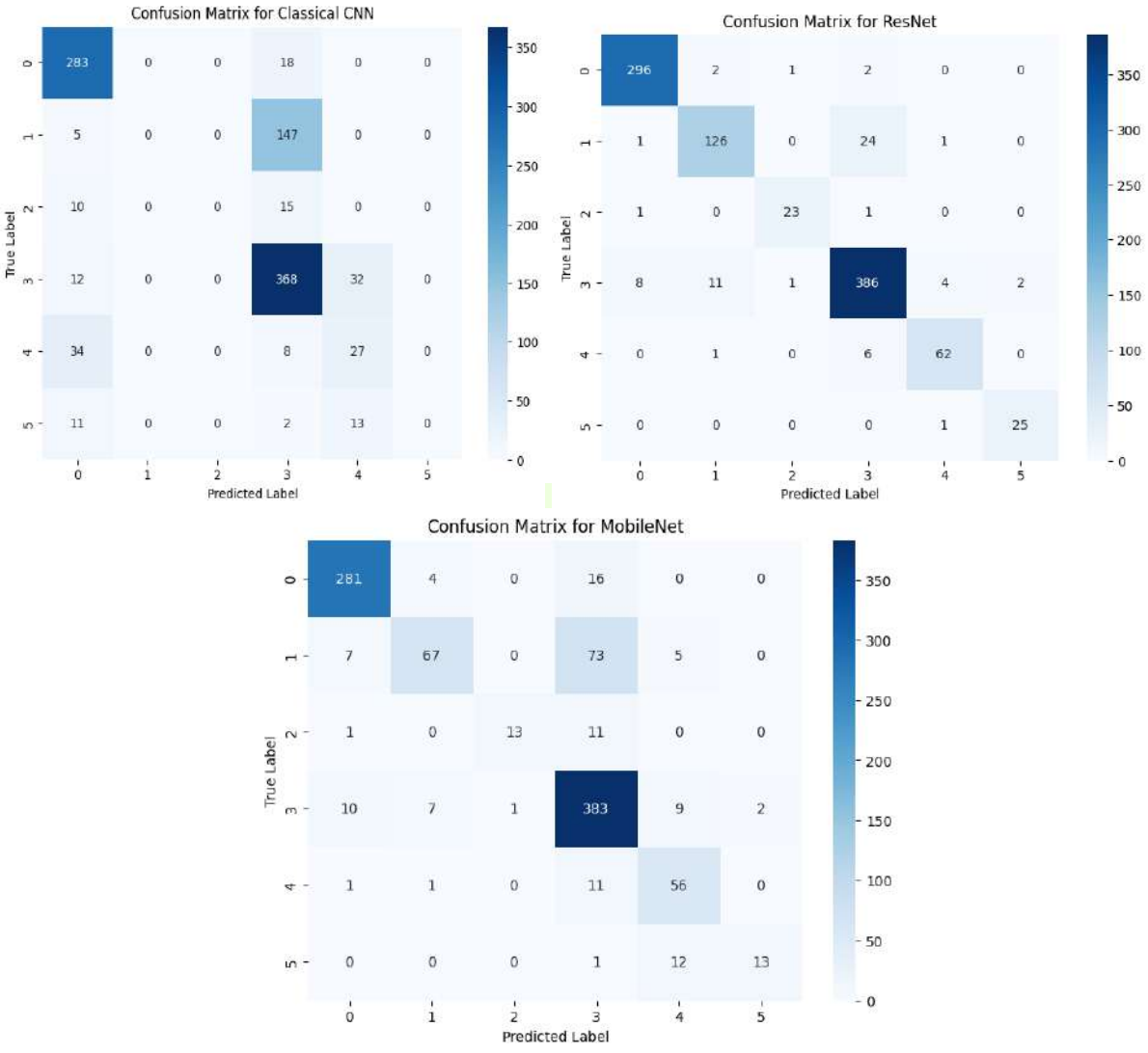

Figure 4: Constructing error matrices results Visualization for adaptive DL models in M1

Rational approaches to improving the accuracy of the loaded models include: fine-tuning by unfreezing the upper layers of the ResNet50 base model and retraining them on additional data; using a smaller learning rate for the unfrozen layers; increasing data variability by applying augmentation techniques such as rotations, brightness adjustments, and horizontal flipping, as well as data mixing (images and labels) to improve model robustness against noise.

Furthermore, there is potential to add additional features, such as the sequence of frames for analyzing the fatigue dynamics, and to increase the number of parameters in the dense layers by adding more layers or neurons to improve the generalization capability of the models.

It is worth noting the consistent decrease in loss and increase in accuracy for each model, indicating the absence of overfitting. The ResNet50 model demonstrates the most stable convergence.

To improve the accuracy of the loaded models, several effective strategies can be considered: fine-tuning by unfreezing the upper layers of the base ResNet50 model and retraining on additional data; using a lower learning rate for the unfrozen layers; increasing data variability through augmentation (such as rotations, brightness adjustments, and horizontal flipping), as well as employing data mixing techniques (images and labels) to improve model robustness against noise.

Additionally, new features can be introduced, such as the sequence of frames for analyzing the dynamics of fatigue, and the number of parameters in the Dense layers can be increased by adding additional layers or increasing the number of neurons, which would enhance the generalization capabilities of the models.

Dependence of values on the number of model training epochs for custom CNN, tuned MobileNet and ResNet is shown in Figure 5.

In M2 we can say, that the difference in model error rates between the training and test sets is minimal, ranging from 3% to 7%, indicating data balance and the high efficiency of fine-tuning models on the constructed datasets using cross-validation.

An analysis of the presented dependencies reveals that the accuracy of the ResNet50 model gradually increases, reaching approximately 0.85 by the end of training, which suggests well-balanced classes and a successful learning process. However, the validation accuracy exhibits some instability: it peaks at around 0.86 during the early epochs but then declines to below 0.80 by the 200th epoch.

This trend may indicate overfitting, as training accuracy continues to increase while validation accuracy decreases.

The accuracy of the MobileNetV2 model initially increases gradually, reaching 0.82 in the later training stages. However, its accuracy improvement is less pronounced compared to other models, and its validation accuracy peaks at 0.84 in the early epochs before declining more significantly than that of ResNet50. This suggests overfitting or potential issues with generalization.

For the EfficientNetB0 model, accuracy also increases with more training epochs, reaching 0.82 in the final stages, albeit at a slower rate compared to other models. Notably, its validation accuracy steadily improves over time, surpassing the training accuracy in later stages and reaching 0.86. This behavior indicates strong generalization capabilities without significant overfitting.

The VGG16 model initially exhibits lower accuracy during training but eventually reaches 0.81. At early stages, its validation accuracy is higher than training accuracy and remains stable at approximately 0.83 by the end of training. This suggests good overall performance, though possible underfitting may need to be addressed.

Summary graph of estimates of training and test accuracies of adaptive DL models is shown in Figure 6.

To test the operation of the created modules and serialized models, test scripts were developed that run the models on prepared videos.

This allowed parallel recognition of driver states in console mode. This approach allows for the prompt analysis of behavioral signs of drowsiness, distraction, and other factors affecting driving safety.

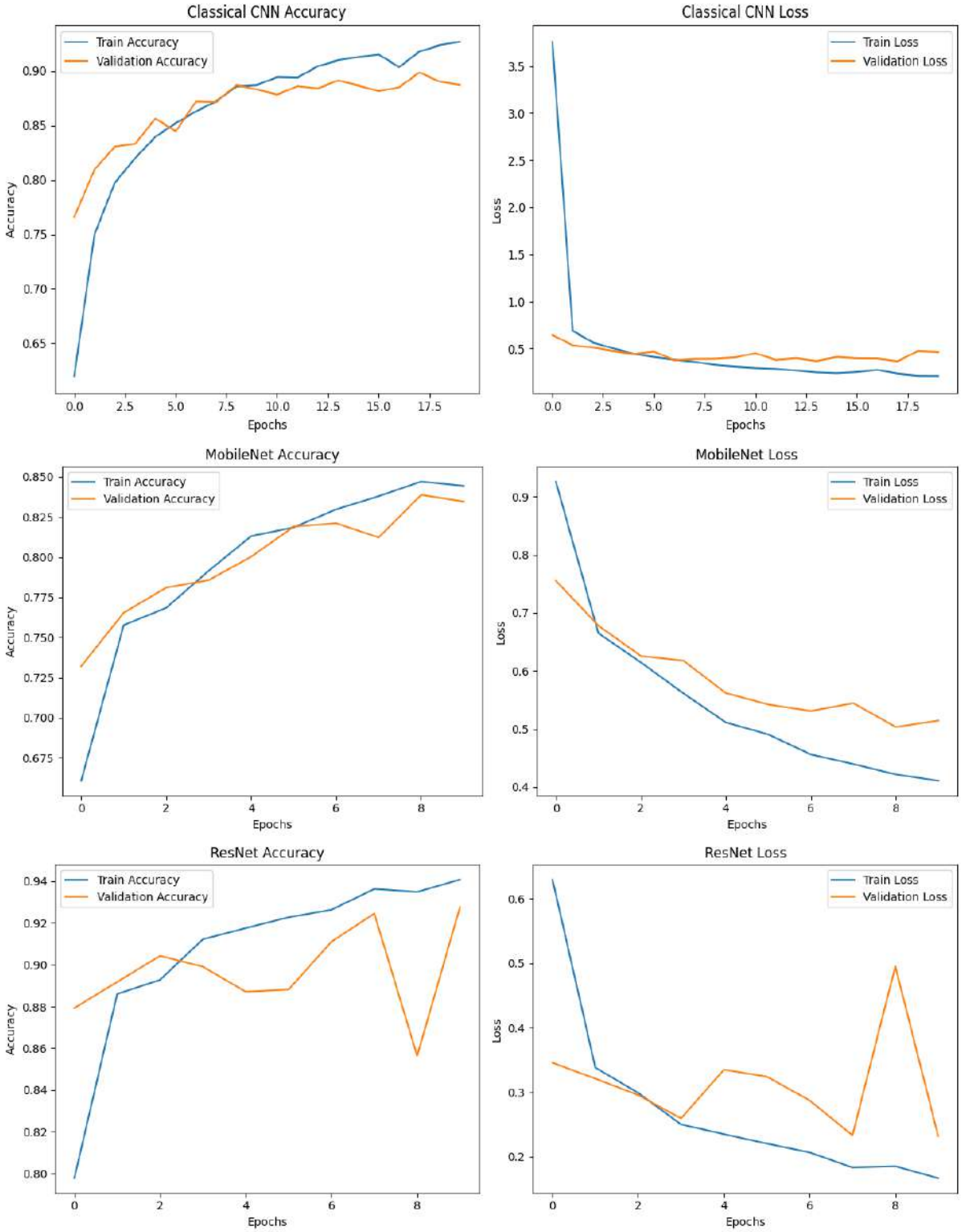

Figure 5: Dependence of values on the number of model training epochs for custom CNN, tuned MobileNet and ResNet

The testing results are presented in Figure 7, where we can see how each module of the system process the video stream and classify the driver's state in real time (evaluates the level of driver's state - drowsiness). Particular attention is paid to the analysis of the stability of the models to changes in lighting conditions, angles, and differences in the anatomical features of vehicle drivers. In summary, the ResNet50 and MobileNetV2 models exhibit signs of overfitting, as the gap between training and validation accuracy increases with more training epochs. In contrast, EfficientNetB0 demonstrates stable performance improvements on both training and validation sets, suggesting its

advantage for this dataset. The VGG16 model maintains consistent but non-optimal results, indicating a potential need for additional hyperparameter tuning or increased training epochs.

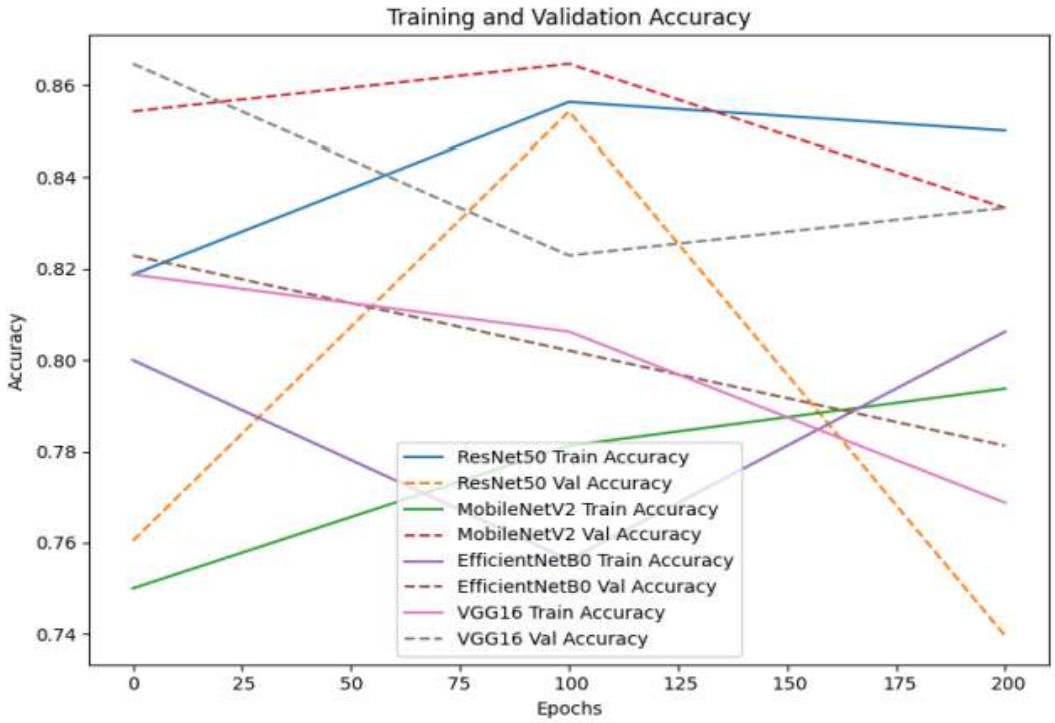

Figure 6: Summary graph of estimates of training and test accuracies of adaptive DL models

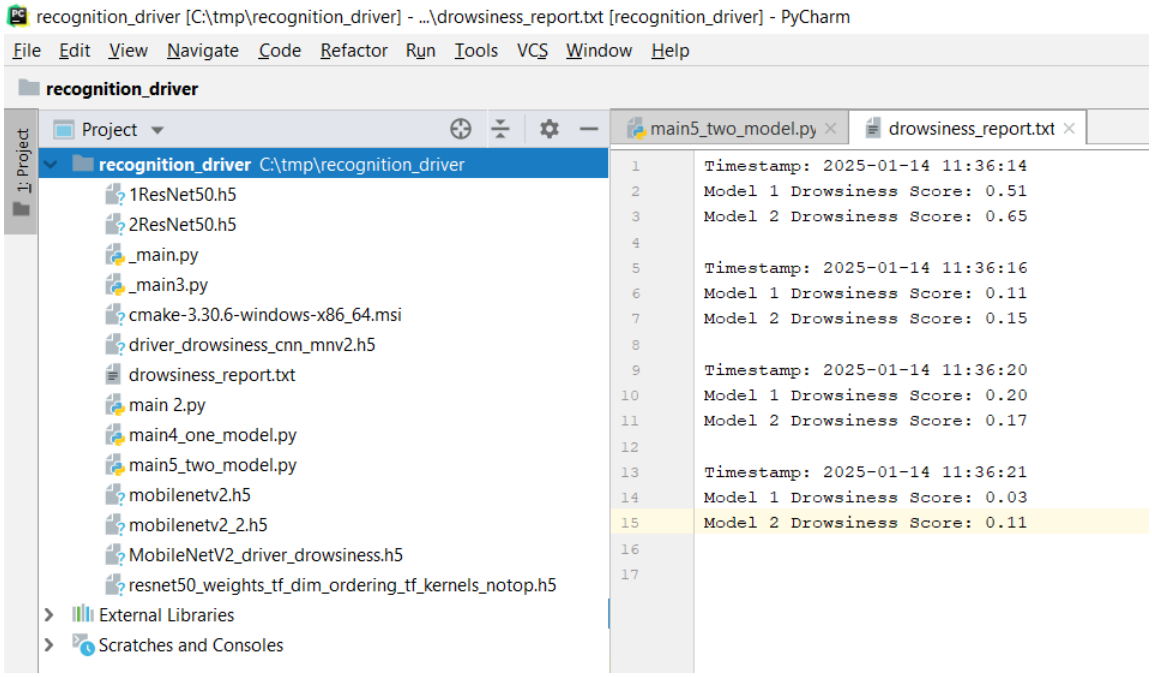

Figure 7: Test enviroment for M1 and M2 usage in PyCharm

5. Conclusions

The research results demonstrate us the effectiveness of fine-tuning and the adaptation of existing DL models, specifically MobileNetV2 and ResNet50, in developed intelligent monitoring system for analyzing vehicle drivers state. By leveraging pre-trained architectures, the models achieve high classification accuracy while reducing computational costs and training time.

The scientific novelty of the developed system lies in the hybrid approach, combining several adaptive deep learning models to improve the accuracy and reliability of real-time driver

monitoring. For the first time, an architecture with two modules based on different convolutional neural networks was implemented, which made it possible to adapt the system to different scenarios and resource constraints. ResNet50, with its residual learning framework, effectively captures complex feature representations but exhibits higher computational demands. In contrast, MobileNetV2, optimized for lightweight and efficient deployment, ensures faster inference while maintaining competitive accuracy, particularly in tasks focusing on eye-region analysis. The results indicate that both models generalize well when fine-tuned on domain-specific datasets, particularly in detecting signs of drowsiness and distraction. As observed, the MobileNetV2 model demonstrates a more accurate assessment of the driver's condition, particularly when analyzing segments containing the ocular region. Moreover, its performance is 2–3 times faster than that of the ResNet50 model. This can be attributed to the fact that ResNet50 considers a broader feature space and possesses a more complex architecture, leading to an increased size of serialized objects and weight values.

However, in cases where the driver's eyes are partially closed or the head is significantly tilted sideways or downward, both models exhibit high confidence levels in detecting driver drowsiness. This finding indicates a high generalization capability of the models and confirms the effectiveness of their fine-tuning on representative datasets. These results suggest that MobileNetV2 may be preferable for resource-constrained real-time systems, whereas ResNet50, due to its deeper architecture, can provide a more detailed analysis of complex scenarios.

Future research efforts should focus on enhancing the accuracy of DL models by implementing the following strategies:

- Integration of multimodal data. Utilizing multiple data sources, such as video recordings, voice signals, biometric indicators, and vehicle movement data, to improve the reliability of driver state assessment.
- Training on large and representative datasets. Expanding the dataset to include a diverse range of drivers across different ages, genders, cultural backgrounds, and driving conditions, ensuring robust generalization.
- Handling rare events. Emphasizing the recognition of rare and critical driver states, such as microsleep episodes or sudden health deterioration, to enhance safety-critical detection capabilities.

A promising direction for the development of the system is the integration of multimodal data and automatic adaptation of the architecture to specific operating conditions.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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Intelligent System and Technology for Optimized Object Placement in Medical and Biological Applications

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Abstract

Intelligent systems for optimized object placement in medical and biological applications leverage artificial intelligence advanced data fusion techniques to enhance precision, efficiency, and patient outcomes. These systems tackle a range of issues, including the positioning of surgical tools, deployment of sensors, and analysis of diagnostic images. Advanced mathematical modeling has become essential in healthcare and biological research, driving innovative solutions for treatment planning and spatial arrangements. This paper introduces an intelligent system aimed at optimizing the placement of geometric objects in medical and biological contexts. We employ a universal mathematical model that functions as an intelligent agent, utilizing parameters to adapt to different scenarios and optimize outcomes. We develop mathematical models and advanced algorithms to ensure precise placement, achieving the desired therapeutic or research outcomes while minimizing adverse effects. The mathematical model is formulated as a knapsack problem and expressed as Mixed Binary Non-Linear Programming (MBNLP). Problems related to optimized object placement can be addressed by selecting different model parameters. Several implementations demonstrate this approach, including Gamma Knife radiosurgery, laser coagulation, brachytherapy, and chromosome territory modeling.

These systems tackle a range of issues, including the positioning of surgical tools, deployment of sensors, and analysis of diagnostic images. Advanced mathematical modeling has become essential in healthcare and biological research, driving innovative solutions for treatment planning and spatial arrangements. This paper introduces a smart system aimed at optimizing the placement of geometric objects in medical and biological contexts.

Keywords

Intelligent system, intelligent technology, optimized geometric design, nonlinear programming, phi-function, cylinder, ellipse, polyhedron, sphere, cuboid,

Introduction

AI-powered intelligent systems are being implemented in the medical and biological fields to achieve improved object placement through artificial intelligence, the Internet of Things, and sophisticated data integration methods. The systems are highly adaptable, addressing various practical challenges such as the strategic placement of surgical tools, efficient sensor deployment, and thorough analysis of diagnostic images.

The utilization of intelligent systems within the medical field is experiencing a marked increase, particularly in medical assessment and treatment design. These systems are invaluable for medical professionals, helping them make more accurate decisions, reduce errors, and improve the effectiveness of therapeutic interventions [1]. Specifically, intelligent systems are used in various tasks such as detailed medical image analysis, personalized treatment planning, epidemic prediction and modeling, and aiding in drug discovery processes [2].

By adjusting the model's parameters, such systems function as intelligent agents, adapting to various scenarios and optimizing their performance. This adaptability and optimization capability are key principles of artificial intelligence, demonstrating how these systems leverage AI techniques to enhance precision and efficiency [3]. The effectiveness of these systems is significantly enhanced

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by mathematical modeling, providing the foundation for simulating complex scenarios and refining decision-making processes [4].

In medicine, mathematical modeling supports diagnostic processes and enhances therapeutic approaches. Differential equation-based models simulate biological systems, offering insights into disease progression and guiding treatment choices [5]. On the other hand, statistical models analyze patient data to forecast disease outcomes and identify the most effective treatments [6]. Advances in this field have significantly transformed healthcare and expanded biological knowledge. More sophisticated systems are now used to develop personalized treatment plans, analyze medical images, and manage workflows, thereby enhancing clinical outcomes and research productivity [7,8].

Automating treatment design marks a significant leap in enhancing the precision, speed, and effectiveness of medical protocols. Healthcare professionals can develop optimized treatment strategies, shorten planning times, and improve patient outcomes. Mathematical modeling in treatment planning is widely used across various medical and biological fields. Automated treatment systems use complex algorithms and mathematical models to define therapeutic targets, ensuring precise delivery of treatments while minimizing harm to healthy tissues.

Gamma Knife radiosurgery is a non-invasive radiotherapy used to treat brain and upper spine conditions. It employs computer-controlled planning to deliver targeted gamma rays to specific areas, minimizing damage to surrounding tissues. This therapy is particularly effective for small brain tumors, vascular malformations, and trigeminal neuralgia. Due to its precision, patients usually require only one treatment session, reducing the need for multiple rounds of radiation therapy. The role of automation and artificial intelligence in radiation therapy planning is further explored in reference [9].

Laser coagulation, also known as laser photocoagulation, is a surgical technique used to treat various eye conditions. It works by cauterizing blood vessels within the eye, commonly used for issues like diabetic retinopathy and retinal tears. The procedure involves using a laser to create tiny burns in the targeted tissues, promoting scar tissue formation that seals the edges of tears and prevents detachment. Laser coagulation effectively slows the progression of retinal disorders, reducing the risk of future vision loss. The article [10] discusses the use of artificial intelligence in diagnostic screening, predicting disease progression, and assessing treatment effectiveness through quantitative methods.

Brachytherapy is a type of internal radiation therapy that treats cancer by placing radioactive materials directly in or near the affected tissue. This method delivers high doses of radiation to the tumor while protecting healthy tissues from excessive exposure. Brachytherapy is used for various cancers, such as prostate, cervical, and breast cancer. Treatments can be temporary or permanent, depending on the type of cancer and the treatment plan. A study in article [11] describes a genetic algorithm that optimizes the placement of radiation seeds, ensuring complete coverage of the prostate and reducing radiation 'hotspots' in the urethra. The accuracy of placing cylindrical radioactive capsules in brachytherapy depends on their orientation and distance from the target tissue. These factors are essential for delivering the radiation dose precisely to the tumor while minimizing exposure to healthy tissues. Proper alignment of the capsules directs the radiation to the tumor, avoiding unnecessary exposure of healthy tissues and improving treatment effectiveness. Additionally, the distance between the capsule and the tumor significantly affects the radiation dose distribution.

Chromosome territory modeling studies the 3D arrangement of chromosomes in the cell's nucleus during interphase. Chromosomes occupy specific areas called chromosome territories and usually arrange themselves in a radial pattern within the nucleus. This organization varies by cell and tissue type and is a conserved trait across evolution. A research paper [12] explores the spatial organization of CTs in mammalian cell nuclei, highlighting the non-random, probability-driven nature of CT arrangement. Researchers model chromosome territories to study their spatial arrangement in the nuclear space. Packing algorithms can adjust the arrangement of overlapping ellipses representing chromosome territories, helping to simulate random or non-random chromosome distribution patterns. This approach enhances understanding of genomic regulation and function.

Packing problems, particularly those requiring optimal arrangement of items within containers without any overlap, frequently rely on nonlinear optimization techniques [13]. These approaches are beneficial for dealing with the complex limitations inherent in these problems. They are designed to determine numerical solutions for arranging various shapes, including circles, spheres,

ellipses, and ovals. Due to the inherent intricacy of such packing scenarios, finding completely accurate solutions is typically unfeasible. Consequently, researchers and practitioners focus on deriving approximate or numerical solutions.

Employing heuristic approaches, which encompass strategies like genetic algorithms, simulated annealing, and tree search methods, is a common practice to refine the quality of numerical results [14]. These heuristic approaches capitalize on specific problem knowledge and operational guidelines to identify approximate solutions for packing scenarios. They are exceptionally useful in handling the intricate nature and computational hurdles of applying non-overlap and containment requirements.

Whether linear or nonlinear, mixed-integer programming models address both the continuous and discrete facets inherent in packing problems [15]. They integrate diverse methodologies such as constraint programming and tailored heuristics to ascertain optimal or near-optimal solutions, specifically for standard allocation, cutting, and packing applications.

This paper introduces an intelligent system designed to simulate the arrangement of geometric entities. This system makes use of a universal model grounded in the phi-functions method [16]. Expressly, normalized phi-functions allows calculating distance between these objects. The method considers object orientation, thereby affording fine-grained control over positioning. By adjusting the model's parameters, the system operates as an intelligent agent, adapting to various scenarios and optimizing object placement. Furthermore, by modulating the model's parameters, users can simulate object placement at defined distances or achieve carefully managed overlaps. The intelligent system's ability to refine and optimize based on input parameters aligns with AI methodologies, providing a robust tool for complex medical and biological applications. This approach transforms placement challenges into the framework of MBNLP [13, 15].

Examples of the system's applicability include optimizing the positioning of radioactive seeds in brachytherapy treatments, planning the arrangement of laser spots in laser coagulation procedures, and modeling the spatial organization of chromosome territories.

Special Universal Mathematical Model and its Characteristics

The foundation of the proposed intellectual system is a distinctive universal mathematical model of optimization geometric design constructed with specialized intellectual means of modeling this category of problems. These intellectual means encompass specific functions designated as "phi-functions" [16]. These functions facilitate the construction of a generalized universal mathematical model in the form of a nonlinear optimization problem.

Let $O_i \in R^d$ $(d=2,3)$ be objects with given metric characteristics m_i, $i \in I_N = \{1,2,\dots,N\}$. We define the location of objects in Euclidean space as $u=(u_1,u_2,\dots,u_N)$ where $u_i=(v_i,\Theta_i)$, $v_i=(x_i,y_i)$ (or $v_i=(x_i,y_i,z_i)$) are coordinates of the poles of O_i and Θ_i are angles, specifying orientations of O_i, $i \in I_N$. We denote the object O_i with placement parameters u_i as $C_i(u_i)$, $i \in I_N$.

The placement region P is specified by given metric characteristics m. Objects O_i, $i \in I_N$ should be packed in P in one of two ways:

- At the minimum admissible distances $d_{ij} \geq 0$, $1 \leq i < j \in I_N$, between themselves and the minimum admissible distances $d_i \geq 0$, $i \in I_N$ to the frontier of P
- With allowing overlap of objects, regulated by parameters $d_{ij} < 0$, $1 \leq i < j \in I_N$, and allowing objects to extend beyond the frontier of P, regulated by parameters $d_i < 0$, $i \in I_N$.

We aim to define a subset from the set O_i, $i \in I_N$, that maximizes the total volume of the objects when placed in P. The mathematical model of the problem is as follows:

$$V^* = \max \sum_{i \in I_N} t_i V(O_i) \text{ s.t. } u \in G \tag{1}$$

where

$$t_i = \begin{cases} 1 \text{ if } \Phi_i(u_i) \geq d_i, \\ 0 \text{ otherwise,} \end{cases} \tag{2}$$

$$G = \left\{ u \in R^{(2d-1)N} : t_i t_j \Phi_{ij}(u_i,u_j) \geq d_{ij},\ 1 \leq i < j \in I_N \right\}. \tag{3}$$

Here, t_i, $i \in I_N$, are binary variables that determine whether an object belongs to P. The inequality $\Phi_i(u_i) \geq d_i$ specifies whether the object O_i satisfies the placement condition relative to the frontier of P. At the same time, the inequality $\Phi_{ij}(u_i, u_j) \geq d_{ij}$ checks whether the conditions for the mutual placement of objects hold.

To solve the problem (1) – (3), it is necessary to construct normalized phi-functions. Generally, this is a complex task, but researchers have already developed such phi-functions for some basic objects [17,18].

MBNLP problems is inherently complex due to the combination of continuous and discrete variables and nonlinear constraints. Solving such problems often involves techniques such as branch-and-bound, which systematically explores the solution space by dividing it into smaller subproblems. However, given the number of variables and constraints, such exhaustive enumeration is impractical. Therefore, we employ heuristic approaches, selecting subsets of objects from the given set that meet the objective function criteria. Subsequently, a block optimization algorithm is applied, which has significantly lower computational complexity compared to branch-and-bound algorithms.

The problem (1) – (3) divides into two stages. In the first stage, we enumerate subsets from the set of all objects. In the second stage, the placement of each subset in P . Then, the placement with the best objective function value is an approximate solution of the problem (1)–(3). According to the typology of Cutting and Packing Problems [19], the problem relates to Knapsack Problem or Identical Item Packing Problem depending on the metric characteristics of the objects. Therefore, to obtain a solution, a sequential addition scheme [20,21] is usually performed, also known as block optimization [22,23]. A method to solve the Knapsack Problem considered in [24] allows for collective rearrangement within the sequential addition scheme. Another challenge is the presence of angles, which specify the orientation of the objects.

Next, we implement the model for some applications in medicine and biology.

Applications in medicine and biology

Planning of Gamma Knife radiosurgery therapy

Gamma knife treatment involves directing beams to a common center to create a radiation dose. The primary geometric difficulty in this treatment involves precisely positioning a series of spheres within a three-dimensional tumor of varying shapes. Significant sphere overlap can lead to excessive dosages, whereas controlled, minor overlap is generally acceptable.

According to the problem (1) – (3), $O_i = S_i \in R^3$ are spheres with given radius r_i, $i \in I_N = \{1,2,\dots,N\}$. $u_i = v_i = (x_i, y_i, z_i)$. There is no need to account for rotation angles Θ_i. We set the parameters $d_{ij} < 0$, $1 \leq i < j \in I_N$, and $d_i < 0$, $i \in I_N$ and consider the placement region P as a convex polyhedron defined by a system of inequalities $A_l x + B_l y + C_l z + D_l \geq 0, l \in L$. Here, $A_l x + B_l y + C_l z + D_l = 0, l \in L$, are the normal equations of planes.

The problem (1) – (3) takes the following form:

$$V^{i} = \frac{4}{3}\pi max \sum_{i \in I_N} t_i r_i^3 \text{ s.t. } u \in G \tag{4}$$

where

$$t_i = \begin{cases} 1 \text{ if } \Phi_i(u_i) \geq d_i, \\ 0 \text{ otherwise,} \end{cases} \tag{5}$$

$$G = \left\{ u \in R^{3N} : t_i t_j \Phi_{ij}(u_i, u_j) \geq d_{ij},\ 1 \leq i < j \in I_N \right\}, \tag{6}$$

$$\Phi_i(v_i, r_i) = min\left\{ A_l x_i + B_l y_i + C_l z_i + D_l - r_i, l \in L \right\},$$

$$\Phi_{ij}(u_i, u_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} - (r_i + r_j).$$

The sequential addition scheme is realized to solve the problem (4) – (6).

We consider a polyhedron with 12 vertices. Table 1 provides the coordinates of the vertices.

Table 1
Coordinates of vertices of P

No.	1	2	3	4	5	6	7	8	9	10	11	12
x	12.14	4.64	-4.64	12.14	-15	-12.14	-4.64	4.64	12.14	15	0	0
y	7.5	-7.5	-7.5	-7.5	7.5	-7.5	7.5	7.5	7.5	-7.5	16.8	-16.8
z	8.82	14.63	14.63	8.82	0	8.82	-14.63	-14.63	-8.82	0	0	0

The number of faces of P is $|L|=20$. Faces are defined by three vertices with numbers 1-11-3, 3-11-5, 5-11-7, 7-11-9, 9-11-1, 1-3-2, 2-3-4, 3-5-4, 4-5-6, 5-7-6, 6-7-8, 7-9-8, 8-9-10, 9-1-10, 10-1-2, 2-12-10, 4-12-2, 6-12-4, 8-12-6, 10-12-8. In this example, we set parameters $d_1=d_2=-3.5$ to ensure controlled overlapping of spheres and their overhanging beyond the treatment area.

Table 2 presents the radii and coordinates of the spheres. Figure 1 illustrates the placement of 15 spheres.

Table 2
Radii and coordinates of spheres in P

No.		x_i	y_i	z_i
1	6.0000	6.0862	9.4494	13.1205
2	6.0000	14.4555	13.8876	6.5106
3	4.0000	11.1704	3.2400	9.5100
4	4.0000	15.4769	7.7476	12.7806
5	4.0000	8.7643	18.0687	11.7612
6	4.0000	5.8567	15.6307	5.8312
7	4.0000	7.9100	8.9659	3.2636
8	4.0000	13.3247	13.9842	15.2371
9	3.0000	13.5530	6.7428	2.1862
10	3.0000	1.8558	15.6172	10.5151
11	3.0000	7.8793	15.8433	17.4366
12	3.0000	15.9303	6.1139	6.858569
13	3.0000	12.1263	7.7394	17.9496
14	3.0000	2.37207	9.8437	6.0495
15	3.0000	5.72614	4.5232	6.9294

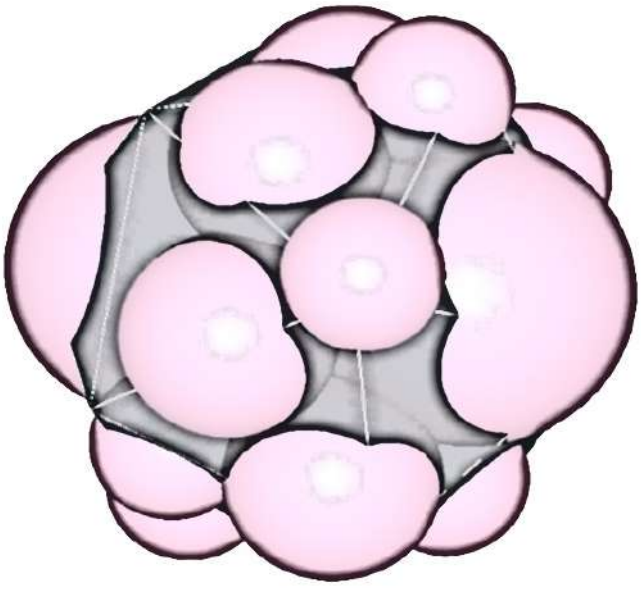

Figure 1: Illustration of target placement

Planning of laser coagulation treatment

Accurately placing photocoagulates (microburns) on the retina is a key geometric task. The photocoagulates must be evenly distributed within the edematous area, avoiding contact with blood vessels and healthy regions. Significant overlap of photocoagulates can lead to excessive dosages, whereas controlled, minor overlap is acceptable.

We model microburns on the retina as equal circles with a given radius and specify a minimum allowable distance between the circles. The placement region consists of convex polygons. This way, the problem can be reduced to solving several subproblems.

According to the problem (1) – (3), $O_i = C_i \in R^2$ are equal circles with given radius r, $i \in I_N = \{1,2,\dots,N\}$. The vectors $u_i = v_i = (x_i, y_i)$ do not involve Θ_i. The parameters $d_{ij} = d_1 \geq 0$, $1 \leq i < j \in I_N$, represent the minimum admissible distance between circles whereas the parameter $d_i = 0$. We consider the placement region P as a convex polygon defined by the system of inequalities $A_l x + B_l y + C_l \geq 0, l \in L$ where $A_l x + B_l y + C_l = 0, l \in L$ are the normal equations.

The problem (1) – (3) takes the following form:

$$V^{\iota} = \pi r^2 \max \sum_{i \in I_N} t_i \text{ s. t. } u \in G \tag{7}$$

where

$$t_i = \begin{cases} 1 \text{ if } \Phi_i(u_i) \geq 0, \\ 0 \text{ otherwise,} \end{cases} \tag{8}$$

$$G = \left\{ u \in R^{2N} : t_i t_j \Phi_{ij}(u_i, u_j) \geq d,\ 1 \leq i < j \in I_N \right\}, \tag{9}$$

$$\Phi_i(v_i, r_i) = min\left\{ A_l x_i + B_l y_i + C_l - r_i, l \in L \right\},$$

$$\Phi_{ij}(u_i, u_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} - 2r.$$

To solve the problem (7) – (9), we implement the sequential addition scheme. The selected placement subregion is quadrilateral with vertices (10,0), (90,5), (69,40), (10,45). Figure 2 shows the treatment region. We set the parameter $d_1 = 1$ to avoid closely spaced microburns. Figure 3 illustrates the placement of 21 circles within the marked convex polyhedron in the placement region shown in Figure 2. Table 3 provides the radii and coordinates of the placed circles.

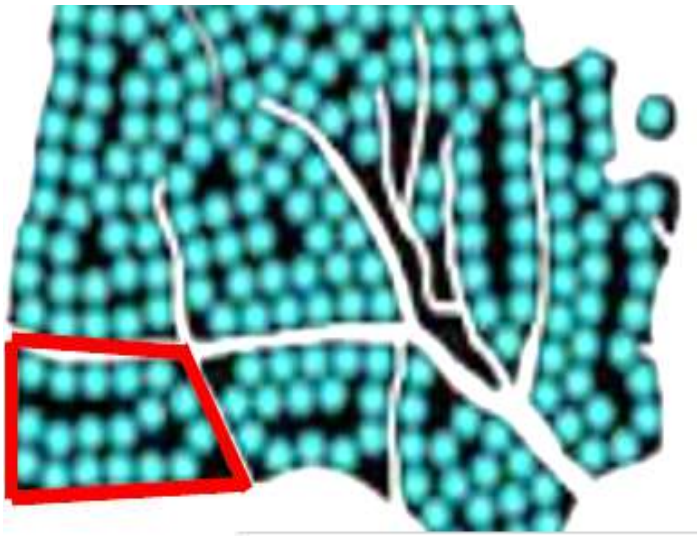

Figure 2: Illustration of the treatment region

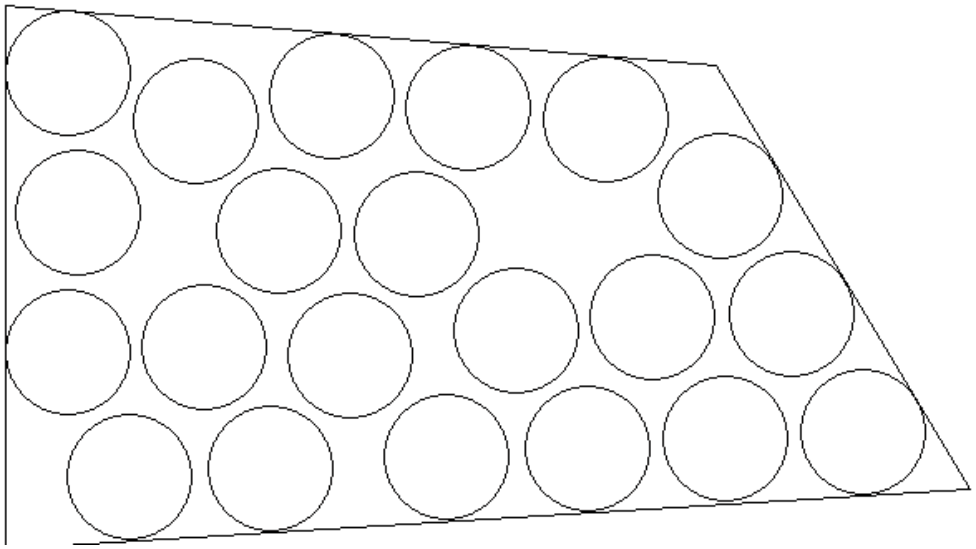

Figure 3: Location of 21 circles

Table 3
Radii and coordinates of circles

No.	5.200	48.505	36.507
1	5.200	26.626	16.626
2	5.200	25.906	35.356
3	5.200	63.776	19.136
4	5.200	16.106	27.791
5	5.200	52.391	18.006
6	5.200	32.094	6.603
7	5.200	44.190	25.944
8	5.200	69.379	29.226
9	5.200	59.874	35.537
10	5.200	37.129	37.436
11	5.200	75.223	19.426
12	5.200	69.710	9.105
13	5.200	46.687	7.618
14	5.200	15.215	16.268
15	5.200	20.309	5.952
16	5.200	15.209	39.319
17	5.200	32.780	26.242
18	5.200	58.312	8.247
19	5.200	81.126	9.663
20	5.200	38.695	15.928
21	5.200	48.505	36.507

Planning of brachytherapy

To achieve precise placement of cylindrical radioactive capsules during brachytherapy, it is necessary to evaluate their location and orientation relative to the target tissue. Correct positioning ensures that the radiation is concentrated on the tumor, avoiding unnecessary exposure of healthy tissues and improving treatment effectiveness.

According to the problem (1) – (3), $O_i = C_i \in R^3$ are equal cylinders with given radius r, and height r, $i \in I_N = \{1,2,\ldots,N\}$, $u_i = (v_i, \Theta_i)$, $v_i = (x_i, y_i, z_i)$, $\Theta_i = (\varphi_i, \omega_i)$. We set the parameters $d_{ij} = d_1 > 0$, $1 \le i < j \in I_N$, as the minimum admissible distance between the cylinders and $d_i = d_2 > 0$,

$i \in I_N$, as the minimum admissible distance to the frontier of P. The placement region P is a convex polyhedron defined by the inequality system $A_l x+B_l y+C_l z+D_l \geq 0, l \in L$, where $A_l x+B_l y+C_l z+D_l=0, l \in L$, are the normal equations.

The problem (1) – (3) takes the following form:

$$V^{\prime}=\pi r_{\square}^2 h \max_{\square} \sum_{i \in I_N} t_i \text{ s.t. } u \in G \tag{10}$$

where

$$t_i=\begin{cases} 1 \text{ if } \Phi_i(u_i) \geq d_2, \\ 0 \text{ otherwise,} \end{cases} \tag{11}$$

$$G=\left\{u \in R^{3N}: t_i t_j \Phi_{ij}(u_i, u_j) \geq d_1,\ 1 \leq i<j \in I_N\right\}. \tag{12}$$

For the problem (10) – (12), we realize the sequential addition scheme as well. We approximate the cylinders with convex polyhedrons and use the normalized phi-functions [17,25]. Figure 4 illustrates the placement of 20 cylinders in a cuboid with dimensions 13.88x12.03x13.65.

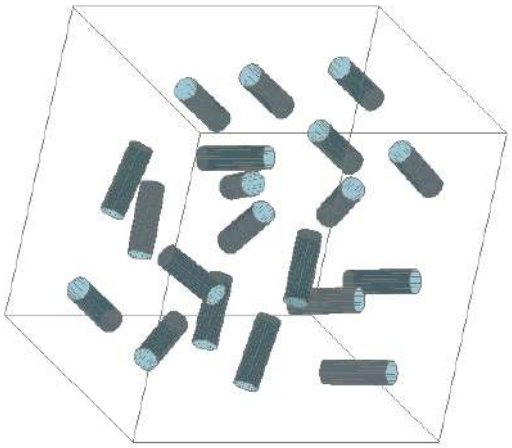

Figure 4: Location of 20 cylinders

Table 4
Coordinates and orientation angles for cylinders placed in P

No.		y_i	z_i	φ_i	ω_i
1					
2	12.645	8.588	5.777	0.014	1.547
3	9.554	5.454	9.421	0.723	-1.206
4	13.637	5.593	13.998	1.585	4.719
5	3.802	5.874	4.351	-1.585	1.578
6	6.797	11.150	10.248	0.643	-1.777
7	4.788	12.608	13.977	-3.142	1.557
8	9.651	5.593	13.656	1.557	1.307
9	3.782	8.463	9.300	0.057	3.142
10	12.651	12.333	4.371	0.000	-1.557
11	13.658	11.584	13.000	1.519	-34.559
12	4.786	4.587	9.257	-3.142	3.364
13	9.782	11.601	13.992	-1.585	1.307
14	12.651	12.608	8.506	3.142	1.557
15	12.751	7.885	9.820	0.792	-1.645
16	8.627	4.587	5.086	-3.142	-0.995
17	3.782	11.660	5.467	-2.519	0.000
18	7.641	8.601	5.357	-3.132	-0.010
19	13.658	4.608	5.357	-3.156	0.000
20	5.691	7.601	13.998	-1.558	61.254

Modeling of chromosome territories

Chromosome territories can be represented as overlapping ellipses within the nucleus, which is approximated by a convex polygon. To model these territories, it is necessary to accurately simulate the spatial distribution and interactions of these ellipses. This involves evaluating their positions and overlaps to reflect the actual behavior of chromosomes during interphase.

According to the problem (1) – (3), $O_i = E_i \in R^2$ are ellipses with half-axes a_i and b_i, $i \in I_N = \{1,2,\dots,N\}$, $u_i = (v_i, \Theta_i)$, where $v_i = (x_i, y_i)$ and $\Theta_i = \varphi_i$. We set the parameters $d_{ij} = d < 0$, $1 \le i < j \in I_N$, and $d_i = 0$, $i \in I_N$, and consider the placement region P as a convex polygon defined by the system of inequalities $A_i x + B_i y + C_i \ge 0, l \in L$. Here, $A_i x + B_i y + C_i = 0$ is the normal equation.

The problem (1)–(3) takes the following form:

$$V^{\prime} = \pi \max \sum_{i \in I_N} t_i a_i b_i \text{ s.t. } u \in G \tag{13}$$

where

$$t_i = \begin{cases} 1 \text{ if } \Phi_i(u_i) \ge d_2, \\ 0 \text{ otherwise,} \end{cases} \tag{14}$$

$$G = \left\{ u \in R^{3N} : t_i t_j \Phi_{ij}(u_i, u_j) \ge d_1,\ 1 \le i < j \in I_N \right\}. \tag{15}$$

We set the parameters to $d_1 = -3$ to allow controlled overlapping of ellipses. Papers [17,18] consider the construction of normalized phi-functions. For the problem (13) – (15), we also implement the sequential addition scheme with collective rearrangement.

Figure 5 illustrates the placement of 10 ellipses within the polyhedron P, with their coordinates presented in Table 5. We consider P as a composition of two convex polyhedrons. Table 6 shows the coordinates and orientation angles of ellipses illustrated in Figure 5.

Table 5
Coordinates of vertices of P

No.	1	2	3	4	5	6	7	8	9	10
x	22	37	47	42	95	91	73	59	12	6
y	9	14	12	4	3	9	27	32	33	32

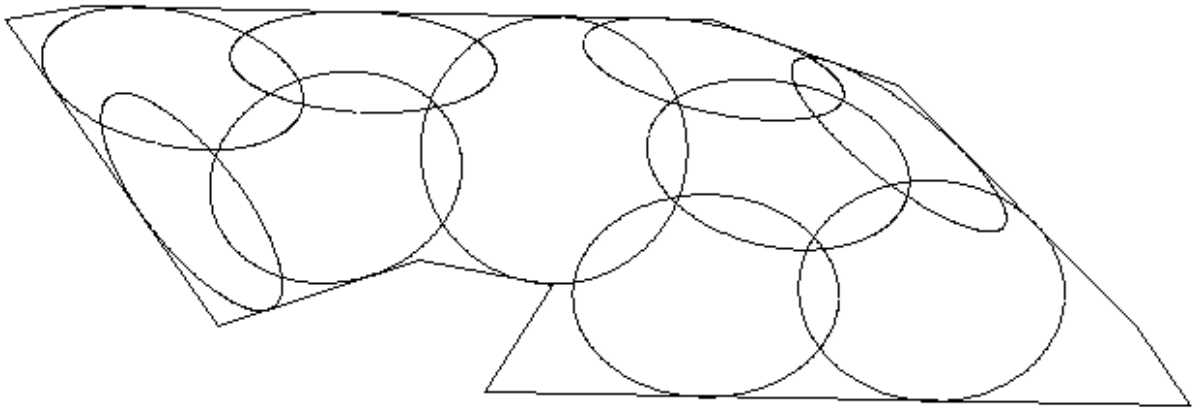

Figure 5. Illustration of placement of 10 ellipses

Discussion

Computational experiments have demonstrated the high adaptability and flexibility of the intelligent system, attributed to its parameterization as an intelligent agent. This adaptability allows the system to optimize object placement across various scenarios effectively.

The computational complexity of the algorithm depends not only on the number of objects being placed but also on the type of phi-functions used. For instance, when placing circles or spheres, the phi-functions are relatively simple, enabling the placement and local reorganization of hundreds of objects. In contrast, when describing interactions between ellipses (or ellipsoids) and cylinders, which are non-oriented and whose placement depends on rotation angles (involving trigonometric functions), the phi-functions have a significantly more complex structure and logical operators. This complexity can substantially impact computational efficiency.

Table 6
Coordinates and orientation angles for ellipses placed in P

No.		b_i	x_i	y_i	φ_i
1	9.578	7.786	-0.267	30.764	20.135
2	5.023	10.000	1.788	18.494	27.563
3	3.765	10.000	1.620	32.820	28.783
4	10.000	3.250	3.358	59.166	28.264
5	10.000	10.000	-1.518	47.175	22.163
6	10.000	6.165	3.357	64.030	21.106
7	10.000	2.801	0.661	73.084	22.612
8	10.000	7.582	0.011	58.580	11.271
9	3.571	10.000	2.472	19.935	18.303
10	10.000	8.262	0.065	75.553	11.635

Additionally, the geometric shape of the placement region significantly influences the complexity of phi-functions and, consequently, the computational complexity. For example, irregular or complex-shaped regions require more intricate phi-functions to accurately describe the spatial relationships and constraints.

In the case of approximating cylinders with polyhedra, the computational complexity is also affected by the accuracy of the approximation, which depends on the number of faces of the polyhedra. Higher accuracy requires more faces, leading to increased computational demands. Therefore, the algorithm can handle the placement of dozens of objects when using the sequential addition scheme (block optimization) and local reorganization (optimization) of placements. This approach ensures that the system remains efficient and effective, even when dealing with the intricate nature of three-dimensional space and the associated computational challenges.

The sequential addition scheme (block optimization) is effective for managing the placement of objects, especially when combined with local reorganization. The ability to perform collective rearrangement within this scheme further enhances the system's effectiveness.

Conclusion

This paper puts forth a proposal for the development of intelligent technologies in the domain of geometric design. These technologies utilize advanced methodologies and instruments for automating and optimizing the processes of placing geometric objects in space. Optimization is achieved by applying these technologies in the context of solving applied problems in medicine and biology.

The proposed universal mathematical model, which utilizes normalized phi-functions, encompasses continuous and combinatorial facets of packaging problems. The model's formulation encompasses the movement and orientations of geometric objects, enabling the modeling of object placement at a distance or their controlled overlap. This model possesses characteristics inherent to AI systems, such as adaptability, automation, and intelligent modeling methods and can be applied for decision-making.

The model's capacity to operate with diverse geometric shapes and placement constraints underscores its potential for addressing a broad spectrum of problems. Employing linear and nonlinear mixed-binary programming methods, in conjunction with constraint programming and heuristics, facilitates the identification of near-optimal solutions for cutting and packing problems.

The model enhances the efficiency of medical treatment and facilitates a more profound comprehension of biological processes.

Examples of application include optimizing the placement of radioactive seeds in brachytherapy, determining optimal laser impact points in laser coagulation, and predicting the behavior of chromosomes in chromosome territory modeling. These applications demonstrate the practical use of the model in medical and biological contexts, highlighting its potential to improve clinical outcomes and research efficiency.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Leveraging Machine Learning to Uncover the Relationship between Diabetes and Alzheimer's Disease Progression

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Abstract

Diabetes Mellitus is a metabolic complex and chronic non-communicable disorder affecting a large population in the world. Different studies have shown the damage caused by Diabetes Mellitus on multiple systems, which leads to complications such as cancer, cardiovascular disorders, and sarcopenia. The changes in insulin, glycaemia, or glucose levels bring multiple changes in the body, including the formation of oxidative species, inflammation, Advanced Glycation End (AGE) products, and hormonal imbalance. In recent times, more attention has been given to the association of Diabetes and cognitive dysfunction because of its increasing prevalence and the severe impact on the lives of diabetic patients. Moreover, the part of different proteins and pathways related to Diabetes that lead to the occurrence of other diseases has been demonstrated.

This research presents a predictive model for the early detection of diabetes-associated cognitive diseases using machine learning techniques. The model utilizes patient health records, lifestyle factors, and diabetes progression data to predict cognitive decline risks. The dataset is pre-processed using statistical analysis, followed by feature selection techniques to optimize the model's performance. Various machine learning algorithms, including decision trees, random forests, and neural networks, are explored to determine the most accurate approach for predictive analysis. The study demonstrates that early detection models can effectively predict diabetes-associated cognitive decline (DACD) onset with high precision, offering a valuable tool for healthcare providers. The results show that predictive models can support timely interventions and personalized treatment plans for at-risk patients.

Keywords

Diabetes Mellitus, Cognitive Dysfunction, Alzheimer's Disease, Dementia, Cognitive Learning, Machine Learning, Predictive Modeling, Explainable AI (XAI), Neural Networks, Deep Learning, Healthcare AI, Chronic Disease Prediction, Dementia Prediction

1. Introduction

Diabetes Mellitus is a metabolic compounded as well as chronic non-communicable disease, which is a growing global issue that has social and economic consequences [1]. It occurs because of the massive demolition of β-cells in the pancreas. The count of sufferers for this multifactorial condition was around 108 million in 1980, which is expected to rise to more than 600 million by 2035 [2]. The pathogenesis for this would include enhancing oxidative stress, mitochondrial dysfunction, inflammatory response, dyslipidemia, and insulin resistance. It is usually suspected to be caused by abnormal abdominal fat deposition and elevated glucose levels. These increased glucose levels lead to cerebral microvascular abnormalities and alterations in the functions of endothelial cells in the brain that form the blood-brain barrier [3]. These changes directly lead to the development of Alzheimer's Disease. Different global data shows that 74.7 million people will be affected by this by the year 2030. Insulin receptors are impaired, and insulin levels in cerebrospinal fluid are found to be elevated in this case of neurological disorder. Its pathophysiology would include the accumulation of β-amyloid proteins in the hippocampus. Patients suffering might lose their ability to perform everyday functions as well, along with the development of neuropsychiatric symptoms. The primary treatment strategy

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for this disorder has been clearing the amyloid β and τ proteins, although no exact treatment is available.

The rising prevalence of Diabetes necessitates early detection methods for DACD to mitigate long-term health implications. Machine learning models offer a promising solution by leveraging data from diverse sources, including clinical records, lifestyle factors, and medical imaging, to predict the likelihood of cognitive decline in diabetic patients. This paper proposes a novel predictive model that integrates multiple data points and advanced machine learning algorithms to provide early detection of DACD [4].

1.1. Co-relation of Diabetes with Cognitive Dysfunction

The first series of cases of association between Cognitive Dysfunction and Diabetes Mellitus was reported in the year of 1922. Patients who developed Diabetes Mellitus (type 1 or type 2) before the age of 4 years were found to have impaired executive skills and difficulty concentrating on work. The predictors of Cognitive Impairment would include the duration of diabetic status (prominence increases with duration of more than 5 years), increased blood group, hypertension, and age group above 51. However, since glucose is the primary substrate for brain energy metabolism then, in the case of Diabetes Mellitus, neurons are unable to store/synthesize glucose, which is initially needed for the systematic circulation and transportation across the blood-brain barrier [5]. So, the brain consumes a large amount of glucose energy, and there is the maximum effect of free radicles, loss of brain cells, and memory function in the brain's hippocampal region. Moreover, as there is an increase of Insulin concentration in the body, this boosts the levels of β-amyloid and senile plaque formation, which leads to Alzheimer's disease. Another aspect would be the increased formation of free radicles [6].

It is found that with Diabetes, the risk of cognitive dysfunction and dementia is increased by 1.5 and 1.6 times, respectively. As per the study conducted by Satyajeet Roy et al. on cognitive function and control of type-2 Diabetes Mellitus in adults, it was found that cognitive dysfunction prevalence was around 65% [7]. The odds of the development of cognitive dysfunction were 9-fold higher in patients affected by Diabetes as compared to non-diabetic ones. This dysfunction was higher in the age group of 51-60. The decreased levels of glycaemic control can occur at any time, regardless of age. These decreased levels enhance the cognitive dysfunction[60]. Brands et al. demonstrated that the complications become worse in patients with other diabetic complications along with Diabetes Mellitus. Patients with type 2 Diabetes Mellitus have reduced psychomotor speed, frontal lobe functioning, verbal memory, complex motor functioning, processing speed, working memory, recalling capabilities, visual retention, and attention. Sinclair et al. found that the score on self-care was lower in patients with mini-mental status. Bruce et al. demonstrated that out of all the older patients with type 2 diabetes, 15% had depression, and 12% had cognitive dysfunction [8].

The occurrence of Diabetes would include Insulin Resistance, Sub-diabetic hyperglycaemia, and prediabetic stress. This leads to insulin signalling pathway impairment, subsequently hindering tyrosine's phosphorylation and Insulin Receptor Substrate (IRS) [9]. This negatively impacts the expression and transcription of specific transcription factors, i.e., Nuclear Factor- κ B (NF-κ B), Cyclic AMP response element binding protein, and Glycogen Synthase Kinase-3 β (GSK-3β). Moreover, increased levels of Advanced Glycation End Products (AGEs) and reactive oxidative species. These reactive oxidative species activate polyol and hexosamine pathways, eventually contributing to Diabetes Associated Cognitive Dysfunction (DACD). Along with this, there is upregulation of CD16 and CD32 due to M1 polarization and increased presentation of Tumor Necrosis Factor (TNF-α), Interleukin-β (IL-1β), and Interleukin-6 (IL-6) as demonstrated in Figure 2. There are 1.5 times more chances of showcasing neurodegeneration with Diabetes, making it a global challenge to face. The accepted clinical symptoms of Diabetes Mellitus would include the loss of strength, polyuria, polydipsia, loss of vision, pruritus, retrobulbar neuritis, paraesthesia, sexual disorders, abdominal pain, loss of appetite, hypertension, and polyphagia. Out of these, any one symptom is elicited in 95% of diabetic patients [10]. Various evidence has proved that, along with genetic and environmental factors, other alterations such as insulin resistance, hypoglycaemia, hyperglycaemia, oxidative stress, hormonal imbalance, age, and hyperphosphorylation [11].

The increasing prevalence of the association of Diabetes with Alzheimer's Disease has brought many eyes to this and requires primary attention at the initial stages only. Predictive models such as Random Forest, Support Vector machines (SVM), and Neural Networks will be used to examine

intricate interactions among various clinical and lifestyle factors and their influence on diabetes complications, primarily cognition-related diseases. Our goal through these advanced techniques is to improve the early screening of Diabetic Associated Cognitive Dysfunction (DACD), therefore increasing patient's health/safety and assisting physicians with managing their patients [12].

2. Related Work

Several studies have focused on the correlation between Diabetes and cognitive decline. Smith et al. [13] explored the neurobiological mechanisms linking Diabetes to dementia, emphasizing the role of glucose metabolism and insulin signalling in the brain. Johnson et al. [14] proposed a predictive model based on clinical data, focusing on the use of logistic regression to assess cognitive impairment risks in diabetic patients. Martinez et al. [15] applied deep learning techniques to longitudinal health records to predict dementia onset in type 2 diabetes patients, reporting an accuracy rate of 85%. ++

Table 1
References

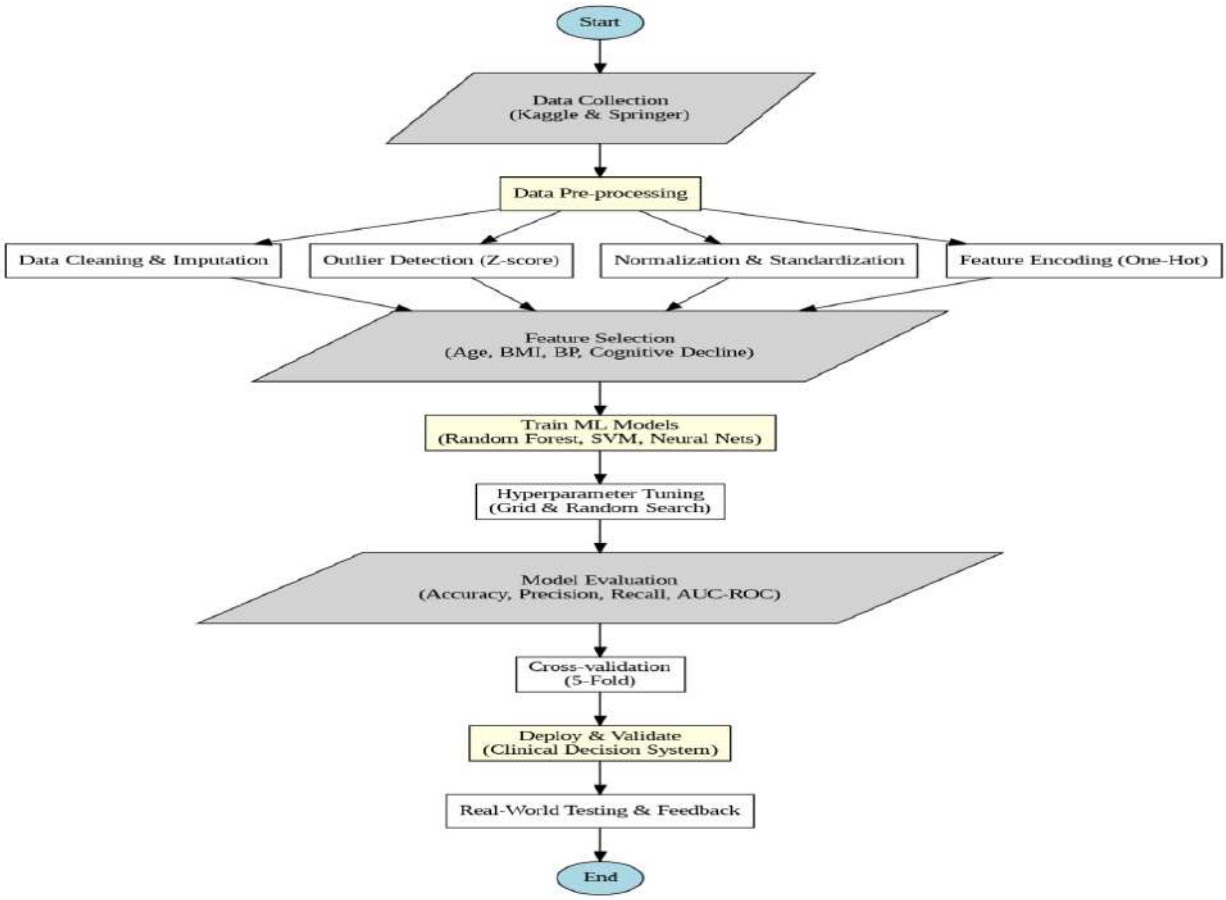
References (16-29)	Title of the study	Author (s)	Study Design	Population selected	Sample Size	Age Range	Main Findings	Key outcomes
1.	Is Diabetes Associated with Cognitive Impairment and Cognitive Decline Among Older Women? (2000)	Edward W. Gregg, PhD; Kristine Yaffe, MD; Jane A. Cauley, DrPH; et al	Prospective Cohort Study	Community-dwelling white women	9679	65-99 years	Women with Diabetes history of more than 15 years has a 57% to 114% greater risk of major cognitive decline as compared to women without Diabetes.	Longer diabetes duration significantly enhances cognitive dysfunction.
2.	Comparison of multiple linear regression and machine learning methods in predicting cognitive function in older Chinese type 2 diabetes patients	Chi-Hao Liu, Chung-Hsin Peng, Li-Ying Huang, Fang-Yu Chen, Chun-Heng Kuo, Chung-Ze Wu, and Yu-Fang Cheng	Test Cohort Study	Older T2DM people	197 (98 male + 99 female)	60-95 years old	ML methods outperformed MLR through random forest (RF), stochastic gradient boosting (SGB), Naïve Byer's classifier (NB) and eXtreme gradient boosting (XGBoost).	RF, SGB, NB, and XG Boost are more accurate than MLR for predicting CFA score and identifying education level, age, frailty score, fasting plasma

								glucose, body fat, and body mass index as important risk factors.
3.	Predicting Cognitive Decline in Diabetic Patients Using Machine Learning	Thompson, A. et al.	Random Forest, Logistic Regression, Support Vector Machine	Diabetic Patients	500 (300 M / 200 F)	50-80 years	Random Forest achieved 82% accuracy, identifying lifestyle factors as key predictors.	Random Forest outperformed Logistic Regression and SVM.
4.	Deep Learning for Early Detection of Diabetes-Related Dementia	Li, Z et al.	Convolutional Neural Networks (CNN)	Diabetic Patients	600 (350 M / 250 F)	45-75 years	CNN identified early signs of dementia with 87% accuracy.	Glucose levels and brain structure changes were major factors
5.	A Predictive Model for Diabetes-Associated Cognitive Disorders Using XG Boost	Zhang, Y. et al.	XG Boost	Diabetic Patients	550 (320 males and 230 females)	40-70 years	XG Boost provided 88% accuracy, identifying insulin resistance as a key factor.	Insulin resistance and hypertension were major predictors.
6.	Hybrid Model of Neural Networks and Decision Trees for Cognitive Impairment in Diabetes	Gupta, S. et al.	Neural Network and Decision Tree Hybrid	Diabetic Patients	550 (250 males and 230 females)	60-85 years	The hybrid model achieved 84% accuracy, particularly in older patients.	Combining decision trees with neural networks improved predictions.
7.	Multimodal Data Integration for Predicting Cognitive Decline in Diabetic Patients	Park, J. et al.	Multi-Layer Perceptron (MLP)	Diabetic Patients	450 (270 males and 180 females)	55-80 years	MLP achieved 86% accuracy using genetic and lifestyle data.	Integration of genetic factors improved prediction.

8.	Prediction of Cognitive Decline in Diabetes Using Temporal Convolutional Networks	Rao, K. et al.	Temporal Convolutional Networks (TCN)	Diabetic Patients	520 (300 male and 220 female)	50-75 years	TCN achieved 85% accuracy by capturing temporal blood glucose patterns.	Temporal glucose fluctuations significantly impacted cognitive function.
9.	Predictive Analytics for Diabetes-Induced Cognitive Impairment Using Ensemble Models	Singh, R. et al.	Ensemble Learning (AdaBoost)	Diabetic Patients	600 (330 males and 270 females)	45-80 years	Ada Boost achieved 89% accuracy, outperforming other ensemble methods.	Boosting models were more effective than bagging for prediction.
10.	Spatio-Temporal Analysis for Predicting Cognitive Decline in Diabetic Patients	Kim, S. et al.	Spatio-Temporal Recurrent Neural Networks (RNN)	Diabetic Patients	530 (290 males and 240 females)	55-85 years	RNN achieved 83% accuracy in analysing spatial and temporal data.	MRI and glucose trends were key factors.
11.	Random Forest-Based Predictive Model for Cognitive Impairment in Type 2 Diabetes	Akhtar, S. et al.	Random Forest	Diabetic Patients	450 (280 males and 170 females)	50-75 years	Random Forest achieved 86% accuracy, identifying diabetes duration and HbA1c as predictors.	Cardiovascular history and HbA1c were key risk factors.
12.	Predicting Dementia in Diabetic Patients Using Explainable AI Models	Wang, L et al.	Gradient Boosting with Explainable AI	Diabetic Patients	500 (290 males and 210 females)	50-80 years	XAI model provided 87% accuracy and interpretability.	Blood pressure variability and glycemic control were key contributors.

While previous research has primarily focused on predictive models for general cognitive decline or specific conditions like Alzheimer's disease, this paper takes a broader approach by incorporating various types of DACD into a single predictive framework. Furthermore, our model extends beyond clinical data by integrating patient lifestyle and behavioural factors to enhance predictive accuracy.

3. Methodology



igure 1: Flowchart for Methodology

3.1. Data Collection and Description

The datasets utilized in this study were collected from three primary sources: One dataset from Kaggle (Dataset 1) and the dataset gleaned from a clinical study published in Springer (Dataset 2). The combined data sets offered complete patient information regarding diabetes progress and cognitive impairment in patients between 61 and 89 years old. Each dataset includes the following key attributes, which are essential for predicting the early onset of Diabetes-Associated Cognitive Diseases (DACD):

- AGE: Ages from 61–89 years in Dataset 1, and 73 ± 6.0 years in Dataset 2.
- GENDER: Data concerning Dataset 1 for both sexes were presented, including 151 males and 169 females.
- ETHNICITY: It includes multivariate populations such as Caucasians, African Americans, Asians, and the rest.
- Educational Background: Literacy levels among the respondents ranged from no KR (kindergarten) to tertiary-level education.
- BMI: The body mass index in the analysis was between 15.6 and 39.1 for Dataset 1 and 25.8 ± 3.9 for Dataset 2.
- LIFESTYLE FACTORS: These are smoking status, alcohol intake, physical activity, and quality of diet consumed.
- Medical History: Traditional data sources contain patient data in terms of a history of depression, hypertension, and cardiovascular diseases, as well as a history of diabetes or cognitive disorders in the family.

- COGNITIVE DECLINE INDICATORS: Memory complaints, confusion, forgetfulness, and other behavioural symptoms were noted.

3.2. Symptom Table and Feature Identification

Table 2
Combined attributes from the datasets, used to construct the predictive model for DACD.

S.No.	Parameters	Dataset 1	Dataset 2
1.	Age (in years)	61-89	73 +- 6
2.	Gender	M=151, F=169	
3.	Ethnicity	Caucasian= 191 African American= 72 Asian= 26 Others= 31	
1	Education	None= 55 High School= 227 Bachelor's Degree= 107 Higher Degree= 28	None=6 High School= 123 Bachelor's Degree= 67 Higher Degree= 1
5.	BMI	15.6-39.1	25.8 +- 3.9
6.	Smoking	75	54
7.	Alcohol Consumption	0.9-19.9	50
8.	Physical Activity	0.8-8.9	
9.	Diet Quality	0.04-9.99	
10.	Sleep Quality	4.0-9.98	
11.	Family History	75	
12.	CVD	54	
13.	Depression	67	
14.	Head Injury	26	
15.	Hypertension	45	
16.	Systolic BP	90-175	137.4+-18.4
17.	Diastolic BP	61-119	72.5+-11.2
18.	Cholesterol Total	151.2-299.8	
19.	Cholesterol LDL	52.7-199.9	91.6+-28.2
20.	Cholesterol HDL	23.4-99.5	52.3+-15.8
21.	Cholesterol Triglycerides	62-389	117.3+-56.3
22.	Functional Assessment	0.7-9.8	
23.	Memory Complaints	67	
24.	Behavioral Problems	44	
25.	Confusion	64	
26.	Disorientation	46	
27.	Personality Changes	52	
28.	Difficulty completing tasks	55	
29.	Forgetfulness	100	

As indicated, the table discusses the significant characteristics used in constructing the model for DACD. These variables were selected based on what signifies Diabetes self-management and what is influential to cognitive functioning, as supported by prior literature and empirical findings.

3.3. Data Pre-Processing

3.3.1. Data Cleaning and Imputation:

So, what exactly do data cleaning and imputation mean? All the missing and incomplete records in the datasets were dealt with for analysis from the two datasets. Mean scores were assigned when scoring non-response on continuous variables like BMI, cholesterol, and blood pressure. For nominal variables such as smoking status and alcohol consumption, the imputations were replaced with the most often occurring class or mode accordingly.

3.3.2. Outlier Detection:

In other words, z-score analysis was used to detect outliers. Outliers were defined as any data points that were at ±3 or more standard deviations away from the mean, and such values were not included in the analysis.

3.3.3. Normalization and Standardization:

Since BMI, cholesterol, systolic blood pressure, and other values are continuous variables, data scaling was applied using Min-Max Scaling to normalize the range of the measure between 0 and 1. For other features that needed more uniformity of variability, the z-score normalization was performed with systolic blood pressure and cholesterol levels standardized within the training data set to have a mean of 0 and a standard deviation of 1.

3.4. Feature Encoding

Gender, smoking status, and family history have been categorized into nominal features, which were encoded to numerical values using the One Hot Encoding method. This step made it possible to limit variations that were suitable for being fed into machine learning models.

3.5. Model Development

3.5.1. Model Selection:

We compared various machine learning algorithms to predict the chances of having DACD.

- Logistic Regression: This is one of the most commonly used algorithms when there are only two classes in which an output label will fit.
- SVM: Support Vector Machines, another kernel-based method that builds linear hyperplanes to separate different classes of data points.
- ADA, Random Forest: Higher and lower test data results are more common with ensemble learning methods, where decision trees come into play.
- DNNs: Convolutional neural networks (CNN) and recurrent neural networks (RNN), are used to find patterns in data that are too complex for other methods.

3.5.2. Model Training:

The pre-processed data was fed and trained on each selected model with suitable hyperparameters. This was done to improve the model performance hyperparameter tuning method by using grid search or random search.

3.5.3. Model Evaluation:

The models were evaluated in a cross-validation experiment to check their generalization on unseen data. The performance of models was evaluated using metrics such as accuracy, precision, and recall, along with F1-score and AUC-ROC.

3.5.4. Model Selection and Refinement:

In the end, we chose the best-performing model. Some might consider adding further refinements, such as feature engineering or ensemble techniques, to enhance the accuracy and robustness of their predictive model.

3.6. Deploy and Validate Model

3.6.1. Incorporation into Clinical Workflow:

The final model was implemented in a clinical decision support system for healthcare professionals. We developed a simple application where users can input patient data and obtain predictions.

3.6.2. Real World Evaluation:

The model's predictive ability was assessed in a real-world setting when applied to predicting DACD in clinical practice. This entailed collecting patient data and comparing the model predictions with what actually occurred..

3.6.3. Ongoing Monitoring and Improvement

The model was iteratively fine-tuned based on data updates and feedback from physicians. To get around this, they slightly changed the model parameters and retrained on a larger dataset.

3.7. Cross Validation and Parameter Tuning

Further, a 5-fold cross-validation method was used to enhance the generalization of the models. There were seven sets for five-folds, each set capable of training on 80% of the data and testing on the left 20%, thus reducing the chances of overfitting. Moreover, the hyperparameters of each model to learn (for example, the number of trees in the Random Forest or the learning rate of the GBM) were tuned using Grid Search and the Random Search method.

3.8. Interpretability of H. Model and Importance of Features

The feature importance level was computed for the Random Forest model. Surprisingly, the analysis of the predictive factors showed that basic characteristics of DACD, including age, BMI, cholesterol, and hypertension, were the most critical factors contributing to its onset. The complete output of the logistic regression model also looked at the readily interpretable coefficients, giving information on the magnitude of influence of each predictor variable on achieving a DACD diagnosis.

4. Result

4.1. Model Performance:

Evaluation metric: Evaluation Metrics: Our proposed Random Forest model achieved an accuracy of 92%, which is a significant improvement over the accuracy reported in 'Diabetes and Dementia'.

igure 2: Random Forest Accuracy

```
Classification Report - Neural Network:
              precision    recall  f1-score   support

           0       0.84      0.90      0.87       277
           1       0.79      0.70      0.74       153

    accuracy                           0.83       430
   macro avg       0.82      0.80      0.80       430
weighted avg       0.82      0.83      0.82       430


Classification Report - Random Forest:
              precision    recall  f1-score   support

           0       0.90      0.98      0.94       277
           1       0.96      0.81      0.88       153

    accuracy                           0.92       430
   macro avg       0.93      0.90      0.91       430
weighted avg       0.92      0.92      0.92       430

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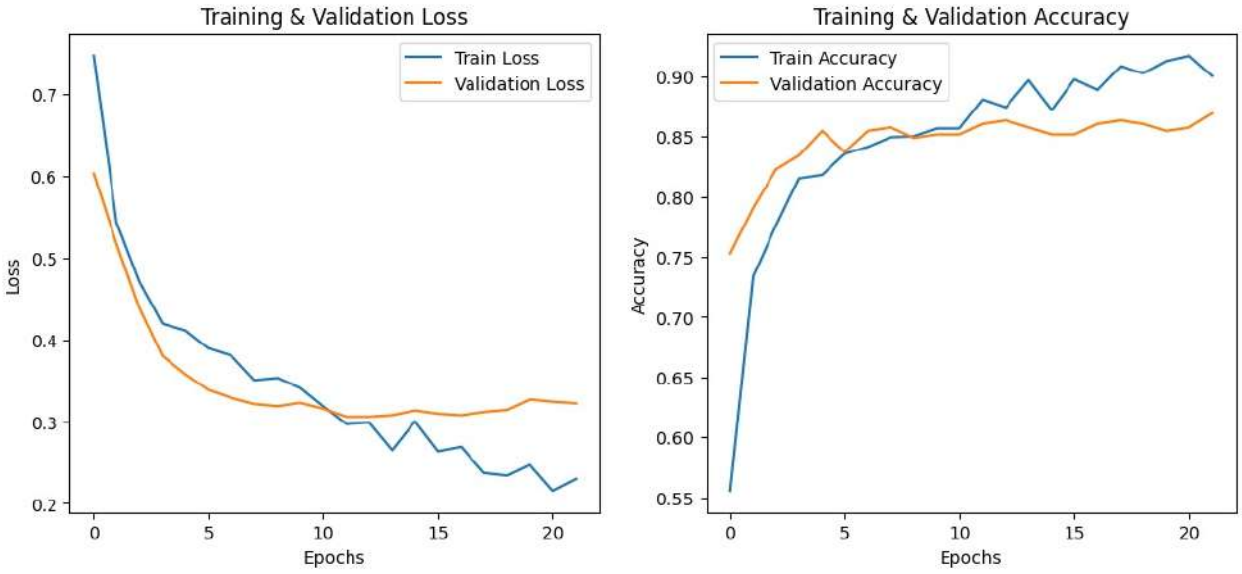
igure 3: Classification report for Neural Network and Random Forest

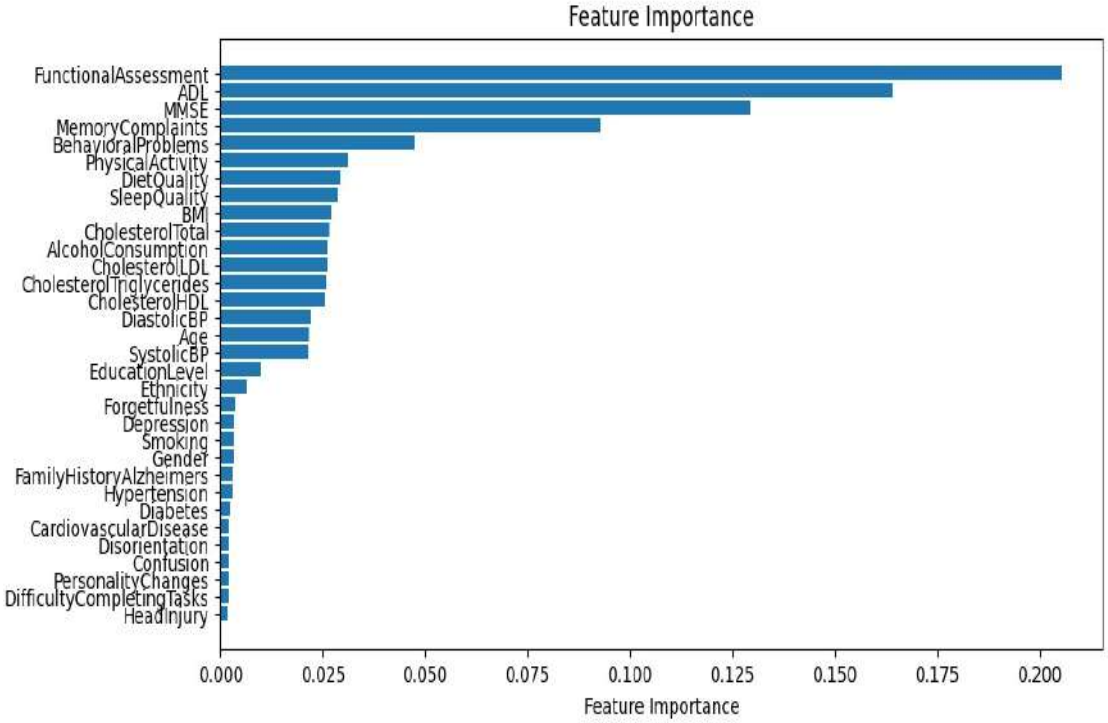


igure 4: Accuracy and Loss Summary for Neural Network

4.2. Feature Importance:

The system was evaluated based on two datasets, from which more than 20 parameters (age, gender, ethnicity, education qualifications, smoking, alcohol consumption, depression, head injury, cholesterol levels, forgetfulness, hypertension, etc.) were selected, highlighting the additional importance of 'Cognitive Function Tests'.

These helped in highlighting the results of the study by determining the development of Alzheimer's Disease in people who have Diabetes of different ages.



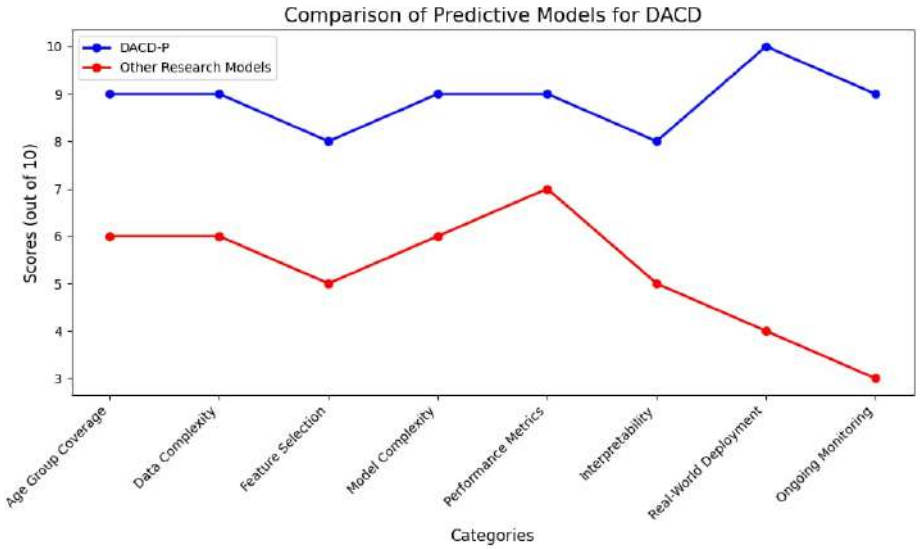
igure 5: Feature Importance

4.3. Comparison Table:

Table 3
Comparison Table

eature	**Diabetes Associated Cognitive Decline-Predictive (DACD-P)**	**Performance of Machine Learning Algorithms for Predicting Progression to Dementia in Memory Clinic Patients**
Objective	Comprehensive early detection of Diabetes Associated Cognitive Decline (DACD)	Predicting dementia onset in Diabetic patients
Data Sources	Multiple sources, including publicly available datasets (Kaggle) and clinical studies (Springer)	Primarily clinical records and longitudinal health data
Age Group	All the age groups (from paediatric to geriatric population), with a significant focus on both early and late cognitive decline risks.	Majorly focused on elderly populations (65+ years).
Features	Incorporates medical, lifestyle, and behavioural factors (age, gender, BMI, smoking, depression, hypertension, cognitive decline indicators (memory, confusion, forgetfulness)).	Primarily clinical factors, for example, glucose levels, insulin resistance, age, gender, BMI, and cognitive test results.
Data Pre-processing	Comprehensive handling of outliers using Z-score analysis, advanced techniques for data cleaning, imputation, and outlier detection.	Basic data imputation using mean values for clinical variables, and includes minimal outlier handling.
Normalization	Min-Max Scaling for continuous variables (ex., BMI, Cholesterol).	Standardization of clinical metrics (ex., Glucose levels).
Feature Encoding	1-Hot Encoding for nominal features (ex., Gender, smoking, family history).	Limited encoding techniques are used.
Machine learning Algorithms	Used ensemble and deep learning methods: Logistic Regression, SVM, Random Forest, CNN, RNN	Primarily, traditional methods like Logistic Regression and Decision Trees. No detailed Optimization methods were mentioned.

	Hyperparameter Optimization using Grid Search and Random Search.	
Model Training and Evaluation	Robust 5-fold Cross-Validation for improved generalization.	Standard train-test split.
Performance Metrics	Comprehensive evaluation using Accuracy, Precision, Recall, F-1 score, AUC-ROC.	Focuses mainly on accuracy and precision.
Model Interpretability	Extensive feature importance analysis (ex., Random Forest feature weights).	No mention of interpretability or feature importance analysis.
Deployment	Designed for seamless integration into the clinical workflows via decision support systems.	No deployment or clinical application was mentioned.
Ongoing Monitoring	Iterative model refinement based on real-world clinical feedback and patient outcomes.	No mention of real-world validation or continuous model improvement.
Accuracy	0.92	0.75
Precision	0.89	0.72
Recall	0.91	0.70
F1 Score	0.90	0.71
AUC-ROC	0.94	0.78
Specificity	0.93	0.76
False Positive Rate (FPR)	0.05	0.12
False Negative Rate (FNR)	0.09	0.15
True Positive Rate (TPR)	0.91	0.70
True Negative Rate (TNR)	0.93	0.76
Log Loss	0.23	0.48



igure 6: Comparison of Predictive Models for DACD

4.4. Discussion:

Incorporating cognitive function tests as features likely contributed to the enhanced accuracy of our model, as these tests directly assess the progression of Alzheimer's disease.

- **Clinical Implications:** Our results suggest that a more comprehensive assessment, including cognitive function tests, can improve the early detection of Alzheimer's disease in patients with Diabetes, leading to treatment at an initial time and potentially better outcomes.

- **Performance Analysis:** The system was evaluated based on two datasets in which more than 20 parameters (age, gender, ethnicity, education qualifications, smoking, alcohol consumption, depression, head injury, cholesterol levels, forgetfulness, hypertension, etc.) were selected. These helped highlight the study's results by determining the development of Alzheimer's Disease in people suffering from Diabetes of different ages.
- **Accuracy of Algorithm:** The Algorithms and machine learning models (Random Forest, Logistic Regression, and Support Vector Machine (SVM)) used are entirely accurate and precise.
- **Scalability:** The system will be able to handle large datasets efficiently.

Acknowledgments

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Modified Kalman Filtering Method for Discrete Signal

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Abstract

Currently, the development of discrete signal filtering methods that are used in computerized biometric identification systems is an urgent task. In the case of linear filtering, one of the most popular methods is the Kalman filter. A modified Kalman filtering method was proposed to improve the efficiency of digital filtering of a discrete signal. This method provides automation of parameter value determination and improves the speed and accuracy of Kalman filtering by using fewer parameters and identifying them based on immune metaheuristic methods. The proposed metaheuristic methods reduce the probability of convergence to a local extremum by using the Cauchy distribution and make parametric identification more accurate. Algorithms of immune metaheuristic methods for identifying Kalman filter parameters have been developed, which are designed for software implementation on the GPU using CUDA technology, which increases the accuracy of Kalman filtering. Further prospects of the study are to utilize the proposed immune metaheuristic methods for various general and special purpose intelligent systems.

Keywords

continuous optimization, immune metaheuristics, artificial immune network, hybrid immune algorithm, parametric identification of Kalman filter

1. Introduction

Currently, it is an urgent task to create digital filtering methods used for noise suppression, which are used in computerized biometric identification systems as well as speech recognition and understanding systems and computer vision [1-2].

One of the popular methods of digital filtering is the use of recurrent neural networks. Such neural networks include NARMANN, ENN, JNN, GRU, LSTM. The disadvantage of such neural networks is the high computational complexity of identifying their parameters due to the lack of the ability to parallelize the learning algorithm, a large number of connections between neurons and the correct choice of activation functions and the number of neurons in the layers.

Another popular digital filtering methods is smoothing adaptive linear filtering [3-4]. For smoothing adaptive linear filtering, the identification of filter parameters plays an important role.

Approximate methods of determining parameter values based on global search do not guarantee convergence. Approximate methods of determining parameter values based on local search have a high probability of hitting a local extremum. Exact methods of determining parameter values have high computational complexity. Thus, the problem of insufficient quality of parametric identification methods arises.

Modern heuristics (or metaheuristics) are used to increase the speed of filter parameter identification and reduce the probability of hitting a local extremum [5-6]. Metaheuristics expand the capabilities of heuristics by combining heuristic methods based on a high-level strategy [7-8]. Metaheuristics often use the behavior of evolutionary and immune approaches [9-10]. Metaheuristics are approximate and, as a rule, stochastic methods [11-12]. The most effective metaheuristics use experience that accumulates during the search process and is stored in memory [13-14].

Object of the study. The process of Kalman filtering of a discrete signal.

Subject of the study. Kalman filtering method for a discrete signal using parametric identification based on immune metaheuristic methods.

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The aim of the work is to improve the quality of Kalman filtering of a discrete signal using immune metaheuristic methods.

To achieve the stated goal, it is necessary to solve the following tasks:

1. Create a modified Kalman filtering method.
2. Develop a continuous optimization method based on an artificial immune network.
3. Create a continuous optimization method based on a hybrid immune algorithm.
4. Conduct a numerical study of the proposed methods of continuous optimization and Kalman filtering.

2. Literature review

In the pre-processing units of modern computer systems for speaker identification, multimodal interface, medical and technical diagnostics, digital filtering methods are implemented that reduce noise and allow analyzing the spectral features of the signal. Various digital filtering methods, from recurrent neural networks to linear digital filters, require the use of methods for determining parameter values. One of the popular approaches is metaheuristic.

Currently, metaheuristics are divided into evolutionary, biological, non-nature-inspired, immune, mathematical, physical, social, chemical. Most metaheuristics use stochastic search, which reduces the probability of hitting a local extremum. Metaheuristics allow solving continuous optimization problems (calculating the point at which the objective function reaches a maximum or minimum) and discrete optimization problems (e.g., clustering, knapsack problem, traveling salesman problem, assignment problem).

Modern metaheuristics have one or more of the following disadvantages:

- the convergence of the method may not be ensured [15-16];
- the iteration number does not affect the solution finding process [17-18];
- only binary potential solutions are used [19-20];
- the metaheuristic method is associated with solving only one problem or there is only an abstract set of operators of this method available [21-22];
- low accuracy of the method [23-24];
- there is no automation of the procedure of identification of method parameters [25-26];
- the method is not intended for solving problems of conditional optimization [27-28].

Based on this, the problem of constructing high quality metaheuristic optimization methods needs to be addressed. One of the most popular ones are immune metaheuristics.

3. Modified Kalman filtering method

In this paper, it is assumed that for each moment of time n the state matrix $\boldsymbol{A}(n)=\boldsymbol{A}$, the control matrix $\boldsymbol{B}(n)=\boldsymbol{0}$, the control vector $\boldsymbol{u}(n)=\boldsymbol{0}$, the process covariance matrix $\boldsymbol{Q}(n)=\boldsymbol{Q}=\boldsymbol{I}_Q\sigma_Q^2$, the observation matrix $\boldsymbol{H}(n)$ are replaced by the vector $\boldsymbol{h}=\boldsymbol{1}_H\sigma_H^2$, the observed noise covariance matrix $\boldsymbol{R}(n)$ is replaced by the scalar σ_R^2, the observation vector $\boldsymbol{z}(n)$ is replaced by the scalar $z(n)$, the observation vector estimate $\acute{\boldsymbol{z}}(n)$ is replaced by the scalar $\acute{z}(n)$, the error vector $\boldsymbol{e}(n)$ is replaced by the scalar $e(n)$, the error vector covariance matrix $\boldsymbol{D}(n)$ is replaced by the scalar $d(n)$, and the optimal Kalman gain matrix $\boldsymbol{G}(n)$ is replaced by the vector $g(n)$. This reduces the amount of computation and the amount of specified data.

The modified Kalman filtering method for a discrete signal consists of the following stages:

1. Initialization.

The initial estimation of the state vector $\acute{\boldsymbol{s}}(0)$ of length m (in this work $\acute{\boldsymbol{s}}(0)=0$) is set. The covariance matrix of the state vector estimate $\boldsymbol{C}(0)$ is set with a size of mxm (in this work, $C(0)$ is filled with uniformly distributed values). In this work, the state matrix $\boldsymbol{A}$ of size mxm, dispersion σ_R^2, dispersion σ_Q^2 for calculating the matrix $\boldsymbol{Q}$ of size mxm, dispersion σ_H^2 for calculating the vector $\boldsymbol{h}$ of length m are set.

2. Forecast stage.

2.1. Calculating the state vector estimate

$$\acute{\boldsymbol{s}}(n-1)=\boldsymbol{A}(n)\acute{\boldsymbol{s}}(n-2)+\boldsymbol{B}(n)u(n). \quad (1)$$

In this work $\boldsymbol{s}(n-1)=\boldsymbol{A}\cdot\boldsymbol{s}(n-2)$.

2.2. Calculating the covariance matrix of the state vector estimate

$$\boldsymbol{C}(n-1)=\boldsymbol{A}(n)\boldsymbol{C}(n-2)\boldsymbol{A}^{\boldsymbol{T}}(n)+\boldsymbol{Q}(n). \quad (2)$$

In this work $\boldsymbol{C}(n-1)=\boldsymbol{A}\cdot\boldsymbol{C}(n-2)\cdot\boldsymbol{A}^{\boldsymbol{T}}+\boldsymbol{Q}$, where $\boldsymbol{Q}=\boldsymbol{I}_{\boldsymbol{Q}}\boldsymbol{\sigma}_{\boldsymbol{Q}}^{\boldsymbol{2}}$.

3. Update stage.

3.1. Calculating the estimate of the observation vector

$$\acute{\boldsymbol{z}}(n)=\boldsymbol{H}(n)\acute{\boldsymbol{s}}(n-1). \quad (3)$$

In this work $\acute{z}(n)=\boldsymbol{h}\cdot\acute{\boldsymbol{s}}(n-1)$, where $\boldsymbol{h}=1_H\boldsymbol{\sigma}_{\boldsymbol{H}}^{\boldsymbol{2}}$.

3.2. Calculating the error vector

$$\boldsymbol{e}(n)=\boldsymbol{z}(n)-\acute{\boldsymbol{z}}(n). \quad (4)$$

In this work $\boldsymbol{e}(n)=\boldsymbol{z}(n)-\acute{\boldsymbol{z}}(n)$.

3.3. Calculating the error vector covariance matrix

$$\boldsymbol{D}(n)=\boldsymbol{H}(n)\boldsymbol{C}(n-1)\boldsymbol{H}^{\boldsymbol{T}}(n)+\boldsymbol{R}(n). \quad (5)$$

In this work $\boldsymbol{d}(n)=\boldsymbol{h}\cdot\boldsymbol{C}(n-1)\cdot\boldsymbol{h}^{\boldsymbol{T}}+\boldsymbol{\sigma}_{\boldsymbol{R}}^{\boldsymbol{2}}$, where$\boldsymbol{h}=1_H\boldsymbol{\sigma}_{\boldsymbol{H}}^{\boldsymbol{2}}$.

3.4. Calculating the optimal Kalman gain matrix

$$\boldsymbol{G}(n)=\frac{\boldsymbol{C}(n-1)\boldsymbol{H}^{\boldsymbol{T}}(n)}{\boldsymbol{D}(n)}. \quad (6)$$

In this work $\boldsymbol{g}(n)=\frac{\boldsymbol{C}(n-1)\boldsymbol{h}^{\boldsymbol{T}}}{\boldsymbol{d}(n)}$, where $\boldsymbol{h}=1_H\boldsymbol{\sigma}_{\boldsymbol{H}}^{\boldsymbol{2}}$.

3.5. Updating the state vector estimate

$$\acute{\boldsymbol{s}}(n)=\acute{\boldsymbol{s}}(n-1)+\boldsymbol{G}(n)\boldsymbol{e}(n). \quad (7)$$

In this work $\acute{\boldsymbol{s}}(n)=\acute{\boldsymbol{s}}(n-1)+\boldsymbol{g}(n)\boldsymbol{e}(n)$.

3.6. Updating the covariance matrix of the state vector estimate

$$\boldsymbol{C}(n)=\boldsymbol{C}(n-1)-\boldsymbol{G}(n)\boldsymbol{H}(n)\boldsymbol{C}(n-1). \quad (8)$$

In this work $\boldsymbol{C}(n)=\boldsymbol{C}(n-1)-\boldsymbol{g}(n)\cdot\boldsymbol{h}\cdot\boldsymbol{C}(n-1)$, where $h=1_H\sigma_H^2$.

4. Selection of criteria for evaluating the effectiveness of the modified Kalman filtering method

In this paper, to evaluate the effectiveness of the modified Kalman filtering method, the accuracy criterion is chosen, which means choosing such values of the parameters $\boldsymbol{A}$, σ_Q^2, σ_H^2, σ_R^2, that provide a minimum root mean square error

$$F=\sqrt{\frac{1}{n^{max}\sum_{n=1}^{n^{mac}}\left(y(n)-\acute{z}(n)\right)^2}}\rightarrow \min_{\boldsymbol{A},\sigma_Q^2,\sigma_H^2,\sigma_R^2}, \quad (9)$$

where $y(n)$ – noise-free countdown,
$\acute{z}(n)$ – observation evaluation,
n^{max} – number of observations.

In accordance with the selected criterion, immune metaheuristic methods for identifying parameters $\boldsymbol{A}$, σ_Q^2, σ_H^2, σ_R^2 are proposed in this paper.

5. Modified artificial immune network method

The artificial immune network was proposed by Timmis, Neal, Hunt and later modified by de Castro, von Zuben and is based on the hypothesis of representing the immune system as an idiotypic network. The disadvantage of the clonal selection theory is that it assumes that a set of cells remains unexcited when there is no antigen.

Scientist Erne proposed a hypothesis according to which the immune system is a regulated network of molecules and cells that recognize each other even in the absence of an antigen. Such structures are often called idiotypic networks, they serve as a basis for studying the behavior of the immune system. Erne's theory is interpreted as a system of differential equations describing the dynamics of the concentration of lymphocyte clones and the corresponding immunoglobulin molecules. The theory of idiotypic regulation is based on the assumption that different lymphocyte clones are not isolated from each other, but maintain communication through interactions of their receptors located on the surface of the lymphocyte.

In formulating the foundations of his theory, Jerne introduced the concepts of formal and functional networks. Formal networks serve to study issues of repertoire (recruitment), dualism and suppression. When considering functional networks, a quantitative picture of the theory is presented.

A probabilistic approach to studying idiotypic networks based on the work of Jerne was proposed by the scientist Perelson. This approach is extremely formalized and is mainly associated with the description of phase transitions. Perelson divided the plane of phase variables of the considered system of equations into a subcritical region, a transition region, and a postcritical region. Over the past 20 years, Jerne's proposed immune network theory has received considerable attention, which has led to a detailed study of many computational aspects of the corresponding mathematical models.

The modified artificial immune network method consists of the following steps:

1. Initialization.

1.1. Setting the search area: cell length M, minimum and maximum values of cell components $x_j^{min_j^{max}}$, $j\in\overline{1,M}$. Setting the maximum number of iterations N, population size K, number of clones L_C.

1.2. Setting the cost function (target function) $F(x)\rightarrow \min_x$, where x – cell (real vector containing A, σ_Q^2, σ_H^2, σ_R^2).

1.3. Setting search parameters: mutation parameter α, compression threshold ε, where $\alpha>0$ (the higher the α, the lower the mutation probability), $\varepsilon>0$. The paper it is proposed to use $\delta\left(x_j^{max_j^{min}}\right)$, $0<\delta<1$, instead of parameter α.

1.4. Creating an initial population P.

1.4.1. Cell number $k=1$, $P=\varnothing$.

1.4.2. Generating a random cell $x_k=(x_{k1},\ldots,x_{kM})$, $x_{kj}=x_j^{min_j^{max_j^{min}}}$, where $U(0,1)$ – a function that returns a standard uniformly distributed random number.

1.4.3. If $x_k\notin P$, then $P=P\cup\{x_k\}$, $k=k+1$.

1.4.4. If $k\le K$, then move to step 1.4.2.

1.5. Determine the best cell by the target function

$$x^{¿} = arg\min_{x_k} F(x_k),\ k \in \overline{1,K}. \tag{10}$$

2. Iteration number $n = 0$.
3. Calculating the affinity of population cells P

$$\Phi(x_k) = 1 - \frac{F(x_k) - \min\limits_{i \in \overline{1,K}} F(x_i)}{\max\limits_{i \in \overline{1,K}} F(x_i) - \min\limits_{i \in \overline{1,K}} F(x_i)},\ \Phi(x_k) \in [0,1],\ k \in \overline{1,K}. \tag{11}$$

4. Order the population P by the target function, i.e. $F(x_k) < F(x_{k+1})$.
5. Determine the best cell by the target function

$$k^{¿} = arg\min_{k} F(x_k),\ k \in \overline{1,K}. \tag{12}$$

6. Determining the global best cell. If $F(x_{k^{¿}}) < F(x^{¿})$, then $x^{¿} = x_{k^{¿}}$.
7. Calculating the average cost value

$$\bar{F}^{source} = \frac{1}{K}\sum_{k=1}^{K} F(x_k). \tag{13}$$

8. Creating the best mutated clones set H.
8.1. Set $k = 1$, $H = \varnothing$.
8.2. Creating clones set $\widetilde{P}_k = \{\widetilde{x}_{kl}\}$ for a population cell x_k.
8.3. Creating mutated clones set $\acute{P}_k$.
8.3.1. Clone number $l = 1$, $\acute{P}_k = \varnothing$.
8.3.2. Creating a cell (the paper proposes to use the Cauchy distribution)

$$\acute{x}_{klj} = \widetilde{x}_{klj} + \delta\left(x_j^{max} - x_j^{min}\right) \cdot Cauchy(0,1),\ j \in \overline{1,M}, \tag{14}$$

where $Cauchy(0,1)$ – a function that returns a standard Cauchy distributed random number.
8.3.3. Cell correction $\acute{x}_{kl}$

$$\acute{x}_{klj} = max¿x_j^{min}, \acute{x}_{klj}¿, \acute{x}_{klj} = min¿x_j^{max}, \acute{x}_{klj}¿,\ j \in \overline{1,M}.$$

8.3.4. Calculating $\acute{P}_k = \acute{P}_k \cup \{\acute{x}_{kl}\}$.
8.3.5. If $l < L_C$, then $l = l + 1$, go to step 8.3.2.
8.4. Determining the best element of set $\acute{P}_k$ by the target function $h_k = arg\min\limits_{\acute{x}_{kl}} F(\acute{x}_{kl})$.
8.5. Calculating $H = H \cup \{h_k\}$.
8.6. If $k < K$, then $k = k + 1$, go to step 8.2.
9. Calculating the average cost value

$$\bar{F}^{mutate} = \frac{1}{K}\sum_{i=1}^{K} F(h_k). \tag{15}$$

10. If $\bar{F}^{mutate} \geq \bar{F}^{source}$, then move to step 8.
11. Compressing the set H and replacing population cells P with elements of the set H.
11.1. Set $k = 1$, $m = 1$.
11.2. Forming the ε - neighborhood of the m^{th} element of the set H

$$U_{h_m,\varepsilon} = \{h_l \vee \rho(h_m, h_l) \leq \varepsilon, l \in \overline{1,K}\}, \tag{16}$$

where ρ – the distance between h_m and h_l (e.g. Euclidean distance).

11.3. If $¿ U_{h_m,\varepsilon} \vee ¿ \varnothing$ or $max\, U_{h_m,\varepsilon} = h_m$, then $x_k = h_m$, $k = k+1$.

11.4. If $m < K$, then $m = m+1$, go to step 11.2.

12. If $k = K$, then move to step 14.

13. Initialization of the last population cells P.

13.1. Calculating $x_k = (x_{k1}, \ldots, x_{kM})$, $x_{kj} = x_j^{min_j^{max_j^{min}}}$.

13.2. If $k < K$, then $k = k+1$, go to step 13.1.

14. If $n < N-1$, then $n = n+1$, go to step 3.

The result is $x^¿$.

6. Algorithm of the modified artificial immune network method

The algorithm of the modified artificial immune network method, designed for implementation on GPU using CUDA technology, is shown in Figure 1.

This block diagram functions as follows.

Step 1 – Set the maximum number of iterations N, population size K, number of clones L_C, parameter δ for generating a new solution, compression threshold ε, where $0 < \delta < 1$, $\varepsilon > 0$.

Step 2 – Create an initial population P, using $K \cdot M$ threads that are grouped into K one-dimensional blocks. Each thread calculates $x_{kj} = x_j^{min_j^{max_j^{min}}}$.

Step 3 – Determine the best cell by the target function $x^¿ = arg\, \min_{x_k} F(x_k)$, $k \in \overline{1,K}$.

Step 4 – Set the iteration number $n = 0$.

Step 5 – Calculate the minimum value of the target function a in the current population P, using K threads that are grouped into one one-dimensional block. In this block, the minimum of K elements of the form $F(x_k)$ is calculated based on the reduction.

Step 6 – Calculate the maximum value of the target function b in the current population P, using K threads that are grouped into one one-dimensional block. In this block, the maximum of K elements of the form $F(x_k)$ is calculated based on the reduction.

Step 7 – Calculate the affinity $\Phi(x_k)$ for each cell x_k of population P, using K threads that are grouped into one one-dimensional block $\Phi(x_k) = \dfrac{b - F(x_k)}{b-a}$.

Step 8 – Order population P by the target function, i.e. $F(x_k) < F(x_{k+1})$.

Step 9 – Determine the best cell by the target function $k^¿ = arg\, \min_{k} F(x_k)$, $k \in \overline{1,K}$.

Step 10 – Determine the global best cell. If $F(x_{k^¿}) < F(x^¿)$, then $x^¿ = x_{k^¿}$.

Step 11 – Calculate the average cost value $\bar{F}^{source}$, using K threads that are grouped into one one-dimensional block. In this block, the sum of K elements of type $\dfrac{F(x_k)}{K}$ is calculated based on the reduction.

Step 12 – Set the cell number $k = 1$.

Step 13 – Create clones set $\widetilde{P}_k = \{\widetilde{x}_{kl}\}$ for population cell x_k.

Step 14 – Generate a mutant clones set $\acute{P}_k$ for a population cell x_k, using $L_C \cdot M$ threads that are grouped into L_C one-dimensional blocks. Each thread calculates $\acute{x}_{klj} = \widetilde{x}_{klj} + \dfrac{1}{\alpha} e^{-\Phi(\widetilde{x}_{kl})} Cauch y(0,1)$.

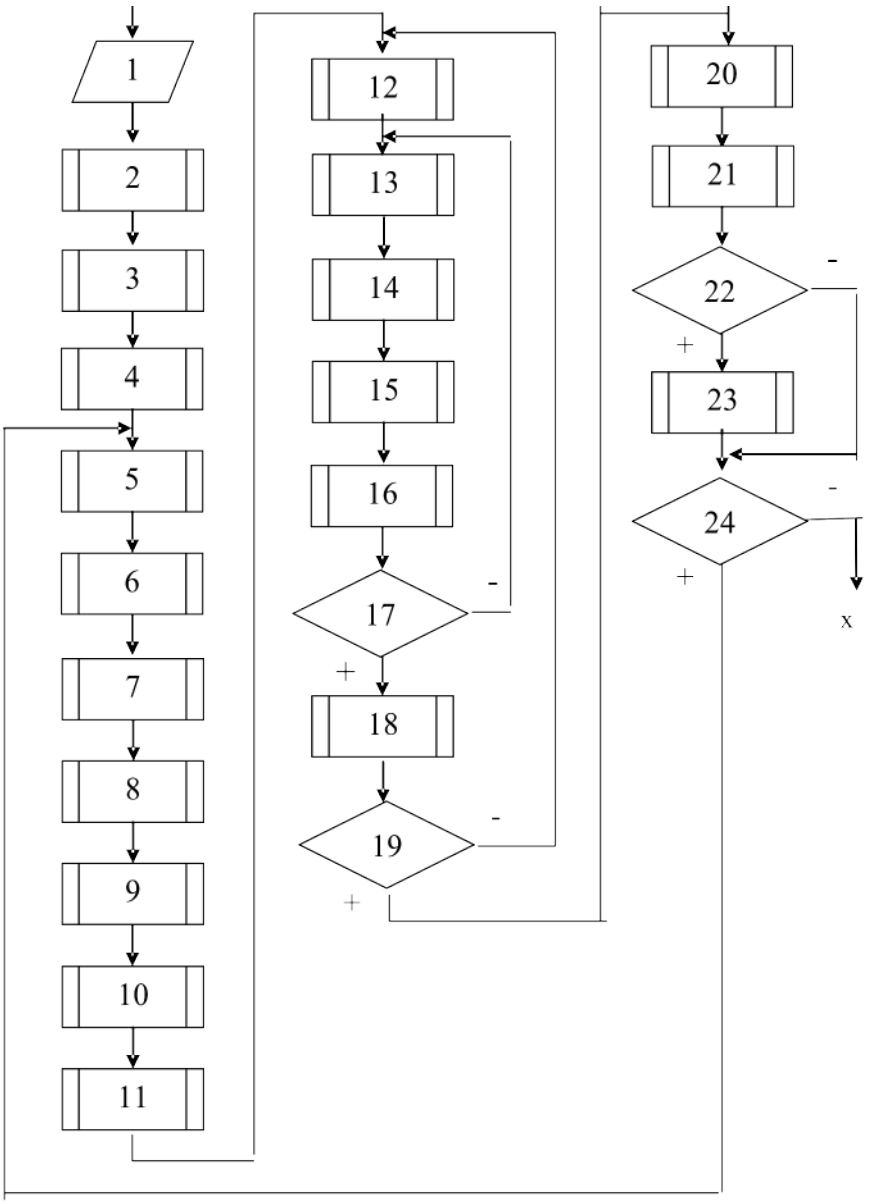

Figure 1: Block diagram of the algorithm of the modified artificial immune network method

Step 15 – Perform the correction of the mutant clones set $\acute{P}_k$ for the population cell x_k, using $L_C \cdot M$ threads, that are grouped into L_C one-dimensional blocks. Each thread calculates $\acute{x}_{klj} = max\left(x_j^{min_{klj}} \right)$, $\acute{x}_{klj} = min\left(x_j^{max_{klj}} \right)$.

Step 16 – Determine the best mutated clone by the target function for each population cell x_k $h_k = arg\min_{\acute{x}_{kl}} F\left(\acute{x}_{kl}\right)$, $l \in \overline{1, L_C}$.

Step 17 – If $k < K$, then $k = k + 1$, go to step 13.

Step 18 – Calculate the average cost value $\bar{F}^{mutate}$, using K threads that are grouped into one one-dimensional block. In this block, the sum of K elements of the form $\frac{F\left(h_k\right)}{K}$ is calculated based on the reduction.

Step 19 – If $\bar{F}^{mutate} \geq \bar{F}^{source}$, then go to step 12.

Step 20 – Compute a distances set $\{\rho\left(h_m, h_l\right)\}$, using $K \cdot K$ threads that are grouped into K one-dimensional blocks. Each thread computes $\rho\left(h_m, h_l\right)$.

Step 21 – Compress set H and replace population cells P with elements of set H.

Step 22 – If $k = K$, then go to step 24.

Step 23 – Initialize the last $K-k$ population cells P, using $(K-k)\cdot M$ threads that are grouped into $K-k$ one-dimensional blocks. Each thread calculates $x_{kj}=x_j^{min_j^{max_j^{min}}}$.

Step 24 – If $n<N-1$, then $n=n+1$, go to step 5.

7. Modified hybrid immune algorithm method

The hybrid immune algorithm was proposed by scientists Lucinska and Wierzchon and is a modification of the artificial immune network. Its distinctive feature is the use of two types of mutations.

The modified hybrid immune algorithm method consists of the following steps:

1. Initialization.

1.1. Setting the search area: cell length M, minimum and maximum values of cell components $x_j^{min_j^{max}}$, $j\in\overline{1,M}$. Setting the maximum number of iterations N, population size K, number of clones L_C, memory size L_M.

1.2. Setting the cost function (target function) $F(x)\to\min\limits_x$, where x – cell (real vector).

11.3. Setting the search parameters: compression threshold ε, maximum cell age a^{max}, memory size excess coefficient α, where $\varepsilon>0$, a^{max} – is a natural number, $\alpha>1$.

1.4. Creating an initial population P.

1.4.1. Cell number $k=1$, $P=\varnothing$.

1.4.2. Generating a random cell $x_k=(x_{k1},\ldots,x_{kM})$, $x_{kj}=x_j^{min_j^{max_j^{min}}}$, where $U(0,1)$ – a function that returns a standard uniformly distributed random number.

1.4.3. Setting the age of cell $a_k=1$.

1.4.4. If $(x_k,a_k)\notin P$, then $P=P\cup\{(x_k,a_k)\}$, $k=k+1$.

1.4.5. If $k\le K$, then move to step 1.4.2.

1.5. Creating the initial set of sets of mutated clones $\{\acute{P}_1,\ldots,\acute{P}_K\}$.

1.5.1. Cell number $k=1$.

1.5.2. Mutated clone number $l=1$, $\acute{P}_k=\varnothing$.

1.5.3. Creating a randomly mutated clone $\acute{x}_{kl}=(\acute{x}_{kl1},\ldots,\acute{x}_{klM})$, $\acute{x}_{klj}=x_j^{min_j^{max_j^{min}}}$.

1.5.4. Generating a random vector of standard deviations $\acute{\sigma}_{klj}=(\acute{\sigma}_{kl1},\ldots,\acute{\sigma}_{klM})$, $\acute{\sigma}_{klj}=U(0,1)$.

1.5.5. If $\acute{x}_{kl}\notin\acute{P}_k\wedge\acute{x}_{kl}\ne x_k$, then $\acute{P}_k=\acute{P}_k\cup\{(\acute{x}_{kl},\acute{\sigma}_{kl})\}$, $l=l+1$.

1.5.6. If $l\le L_C$, then move to step 1.5.3.

1.5.7. If $k<K$, то $k=k+1$, go to step 1.5.2.

1.6 Initializing a set of memory cells $Q=\varnothing$.

2. Iteration number $n=0$.

3. Creating the best mutated clones set $H^{\square}$.

3.1. Cell number $k=1$, $H=\varnothing$.

3.2. Creating a set of clones $\widetilde{P}_k=\{(\tilde{x}_{kl},\tilde{a}_{kl})\}$ for a population cell (x_k,a_k).

3.3. Modification of a set of mutated clones $\acute{P}_k$.

3.3.1. Clone number $l=1$.

3.3.2. Set $\lambda=U(0,1)$.

3.3.3. If $\lambda>0.2$, then calculation of the vector of standard deviations

$$\acute{\sigma}_{klj}=\begin{cases}2(\tilde{x}_{lkj}-\acute{x}_{klj}), & F(\acute{x}_{klj})<F(\tilde{x}_{klj})\\ \acute{\sigma}_{klj}, & F(\acute{x}_{klj})\ge F(\tilde{x}_{klj})\end{cases},\ j\in\overline{1,M}, \tag{17}$$

creation of a cell (the work suggests using the Cauchy distribution)

$$\acute{x}_{klj}=\acute{\sigma}_{klj}Cauchy(0,1)+\tilde{x}_{klj},\ j\in\overline{1,M}, \tag{18}$$

where $Cauchy(0,1)$ – a function that returns a standard Cauchy distributed random number.

3.3.4. Cell correction $\acute{x}_{kl}$

$$\acute{x}_{klj}=max\left\{x_j^{min_{klj}}\right\},\ \acute{x}_{klj}=min\left\{x_j^{max_{klj}}\right\},\ j\in\overline{1,M}.$$

3.3.5. If $\lambda\le 0.2$, then $\acute{x}_{kl}=\tilde{x}_{kl}$, $j=round\left(1+\left(M-1\right)U\left(0,1\right)\right)$, $\acute{x}_{klj}=x_j^{min_j^{max_j^{min}}}$.

3.3.6. If $l<L_C$, then $l=l+1$, go to step 3.3.2.

3.4. Determining the best mutated clone of set $\acute{P}_k$ by the target function

$$h_k=arg\min_{\acute{x}_{kl}}F\left(\acute{x}_{kl}\right). \tag{19}$$

3.5. Calculating $H=H\cup\left\{h_k\right\}$.

3.6. If $k<K$, then $k=k+1$, go to step 3.2.

4. Modification of population P.

4.1. Cell number $k=1$.

4.2. If $F\left(h_k\right)<F\left(x_k\right)$, then $x_k=h_k$, $a_k=1$.

4.3. If $F\left(h_k\right)\ge F\left(x_k\right)$, then $a_k=a_k+1$.

4.4. If $k<K$, then $k=k+1$, go to step 4.2.

5. Adding cells from population P, that have reached age a^{max}, to the set of memory cells Q.

5.1. Set $k=1$, $i=\left\{Q\right\vee+1$.

5.2. If $a_k\ge a^{max}$, then $q_i=x_k$, $Q=Q\cup\left\{q_i\right\}$, $i=i+1$, and in population P pair $\left(x_k,a_k\right)$ is initialized, i.e. $x_{kj}=x_j^{min_j^{max_j^{min}}}$, $j\in\overline{1,M}$, $a_k=1$.

5.3. If $k<K$, then $k=k+1$, go to step 5.2.

6. If $\left\{Q\right\vee\left\{\alpha\cdot L_M$, then move to step 8.

7. Set compression Q.

7.1. Set $i=1$, $m=1$, $\breve{Q}=\varnothing$

7.2. Formation of the ε -neighborhood of the i^{th} element of the set Q

$$U_{q_i,\varepsilon}=\left\{q_l\vee\rho\left(q_i,q_l\right)\le\varepsilon,l\in\overline{1,\vee Q\vee\left\{}\right\}, \tag{20}$$

where ρ – the distance between q_i and q_j (e.g. Euclidean distance).

7.3. If $\left\{U_{q_i,\varepsilon}\vee\left\{\varnothing\right.\right.$ or $max\,U_{q_i,\varepsilon}=q_i$, then $\breve{q}_m=q_i$, $m=m+1$, $\breve{Q}=\breve{Q}\cup\left\{\breve{q}_m\right\}$.

7.4. If $i<L_M$, then $i=i+1$, go to step 7.2.

7.5. Set $Q=\breve{Q}$.

7.6. Order the set Q by the target function, i.e. $F\left(q_i\right)<F\left(q_{i+1}\right)$.

7.7. If $\left\{Q\vee\left\{L_M\right.\right.$, then remove from the ordered set Q the last worst $\left\{Q\vee-L_M\right.$ cells by the target function.

8. Determining the best memory cell of the set Q by the target function

$$x^{\left\{\right.}=arg\min_{q_i}F\left(q_i\right). \tag{21}$$

9. If $n<N-1$, then $n=n+1$, go to step 3.

The result is $x^{\left\{\right.}$.

8. Algorithm of the modified hybrid immune algorithm method

The algorithm of the modified hybrid immune algorithm method, designed for implementation on GPU using CUDA technology, is shown in Figure 2.

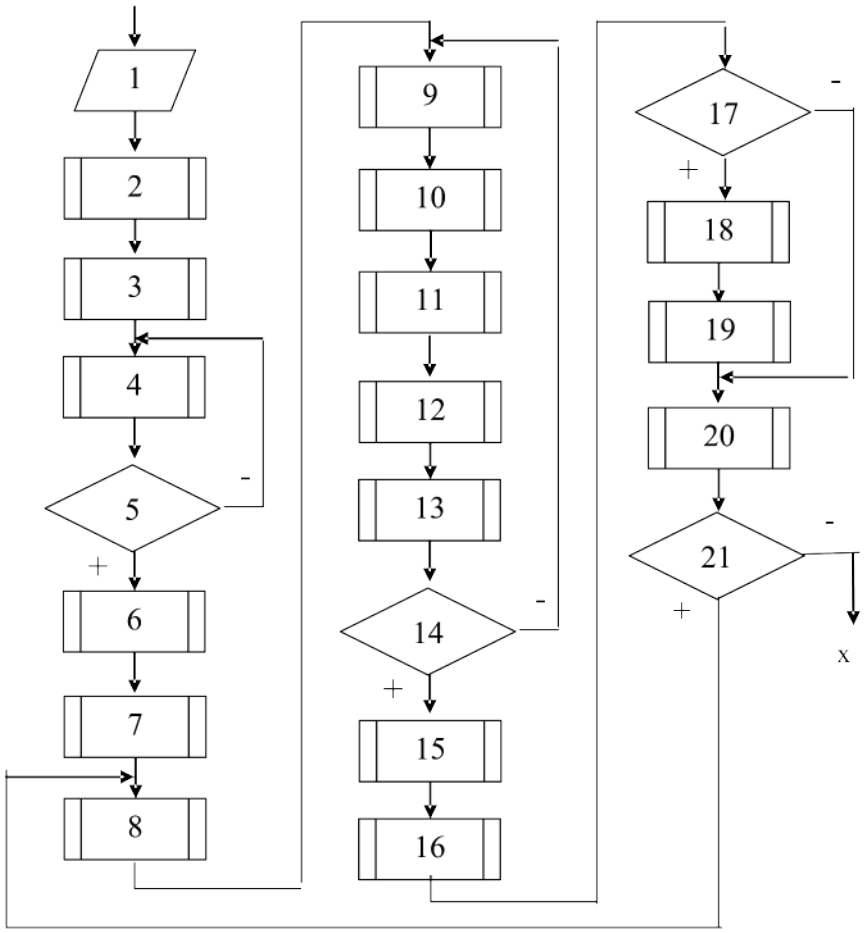

Figure 2: Block diagram of the algorithm of the modified hybrid immune algorithm method

This block diagram functions as follows.

Step 1 – Set the maximum number of iterations N, population size K, number of clones L_C, memory size L_M, compression threshold ε, maximum cell age a^{max}, memory oversize factor α, where $\varepsilon>0$, a^{max} is a natural number, $\alpha>1$.

Step 2 – Create an initial population $P=\{(x_k, a_k)\}$, using $K \cdot M$ threads that are grouped into K one-dimensional blocks. Each thread of each k^{th} block calculates $x_{kj}=x_j^{min_j^{max_j^{min}}}$, $a_k=1$.

Step 3 – Set the cell number $k=1$.

Step 4 – Generate a set of mutated clones $\acute{P}_k=\{(\acute{x}_{kl}, \acute{\sigma}_{kl})\}$, using $L_C \cdot M$ threads that are grouped into $L_C$one-dimensional blocks. Each thread calculates $\acute{x}_{klj}=x_j^{min_j^{max_j^{min}}}$, $\acute{\sigma}_{klj}=U(0,1)$.

Step 5 – If $k<K$, then $k=k+1$, go to step 4.

Step 6 – Initialize a set of memory cells $Q=\varnothing$.

Step 7 – Set the iteration number $n=0$.

Step 8 – Set the cell number $k=1$.

Step 9 – Create clone set $\widetilde{P}_k=\{\widetilde{x}_{kl}\}$ for population cell (x_k, a_k).

Step 10 – Calculate $\lambda_l=U(0,1)$, $l\in\overline{1, L_C}$.

Step 11 – Modify the set of mutated clones $\acute{P}_k$ for population cell (x_k, a_k), using $L_C \cdot M$ strands that are grouped into $L_C$one-dimensional blocks. Each strand of each l^{th} block calculates:

$$\text{If } \lambda_l>0.2, \text{ then } \acute{\sigma}_{klj}=\begin{cases} 2(\widetilde{x}_{lkj}-\acute{x}_{klj}), & F(\acute{x}_{klj})<F(\widetilde{x}_{klj}) \\ \acute{\sigma}_{klj}, & F(\acute{x}_{klj})\geq F(\widetilde{x}_{klj}) \end{cases}, \acute{x}_{klj}=\acute{\sigma}_{klj} Cauchy(0,1)+\widetilde{x}_{klj},$$

$$\text{If } \lambda_l\leq 0.2, \text{ then } \acute{x}_{kl}=\widetilde{x}_{kl},\ j=round(1+(M-1)U(0,1)),\ \acute{x}_{klj}=x_j^{min_j^{max_j^{min}}}.$$

Step 12 – Perform the correction of the modified set of mutated clones $\acute{P}_k$ for the population cell (x_k, a_k) using $L_C \cdot M$ strands, which are grouped into L_C one-dimensional blocks. Each thread of each l^{th} block calculates:

$$\text{If } \lambda_l > 0.2, \text{ then } \acute{x}_{klj} = max\{x_j^{min_{klj}}\}, \acute{x}_{klj} = min\{x_j^{max_{klj}}\}.$$

Step 13 – Determine the best mutated clone by the target function for each population cell (x_k, a_k)

$$h_k = arg\min_{\acute{x}_{kl}} F(\acute{x}_{kl}), l \in \overline{1, L_C}.$$

Step 14 – If $k < K$, then $k = k + 1$, go to step 9.

Step 15 – Modify population P using K threads that are grouped into one one-dimensional block. Each thread calculates:

$$\text{If } F(h_k) < F(x_k), \text{ then } x_k = h_k, a_k = 1, \text{ If } F(h_k) \geq F(x_k), \text{ then } a_k = a_k + 1.$$

Step 16 – Add population P cells that have reached the age a^{max} to memory cell set Q.

Step 17 – If $\{Q \vee \{\alpha \cdot L_M$, then move to step 20.

Step 18 – Compute distance set $\{\rho(q_i, q_l)\}$ using $Q \cdot Q$ threads that are grouped into Q one-dimensional blocks. Each thread calculates $\rho(q_i, q_l)$.

Step 19 – Compress set Q.

Step 20 – Determine the best memory cell of the set Q by the target function $x^{\{} = arg\min_{q_i} F(q_i)$, $k \in \overline{1, K}$.

Step 21 – If $n < N - 1$, then $n = n + 1$, go to step 8.

9. Experiments and results

The numerical study of the proposed metaheuristic methods was carried out using the Python package in the Google Colab environment. Numerical experiments were carried out using the CUDA parallel information processing technology on a GeForce 920M video card with 1025 threads in a one-dimensional block.

In this work, the following parameters were used for the modified artificial immune network method: the maximum number of iterations $N = 100$, population size $K = 20$, number of clones $L_C = 10$, parameter for generating a new solution $\delta = 0.1$, and compression threshold $\varepsilon = 0.1$.

In this work, the following parameters were used for the modified hybrid immune algorithm method: maximum number of iterations $N = 100$, population size $K = 20$, number of clones $L_C = 10$, memory size $L_M = 10$, compression threshold $\varepsilon = 0.1$, maximum cell age a^{max}, and memory oversize factor $\alpha = 1.5$.

In the work, a one-dimensional signal was generated, to which additive Gaussian noise with zero mathematical expectation and dispersion of 135 was added.

In the work, the following root mean square errors were calculated based on the formulas:

$$RMS_{yz} = \sqrt{\frac{1}{200}\sum_{n=1}^{200}(y(n) - z(n))^2}, \quad (22)$$

$$RMS_{x\acute{z}} = \sqrt{\frac{1}{200}\sum_{n=1}^{200}(x(n) - \acute{z}(n))^2}, \quad (23)$$

where $y(n)$ – noise-free countdown,

$z(n)$ – observation (noise-free countdown),

$\acute{z}(n)$ – observation evaluation.

Table 1 presents the root mean square errors for immune metaheuristic methods. For all three methods RMS_{yz}=9.25.

Table 1

Root mean square errors

Immune metaheuristic methods	$RMS_{x\dot{z}}$
Clonal selection method	4.9
Modified artificial immune network method	4.5
Modified hybrid immune algorithm method	3.8

For example, for the modified hybrid immune algorithm method, the following parameter values were obtained:

$$A=\begin{bmatrix}1.6 & -0.8\\ 1 & -0.3\end{bmatrix},\ \sigma_Q^2=0.35,\ \sigma_R^2=4.16,\ \sigma_H^2=0.38.$$

Figure 3 shows the original signal without noise and the signal with noise (observation).
Figure 4 shows the original signal without noise and the observation estimate signal.

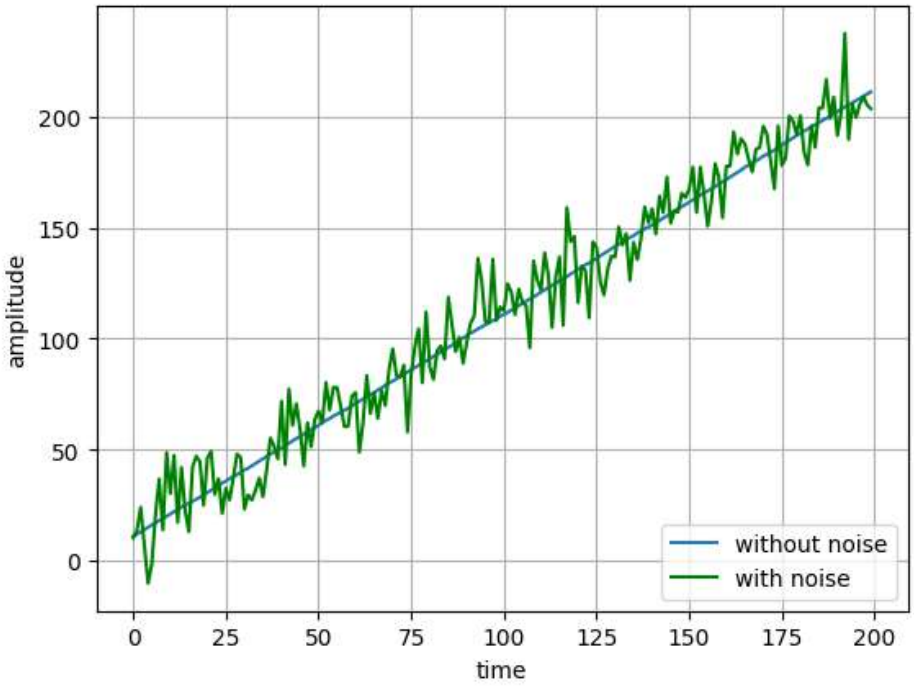

Figure 3: Original signal without noise and signal with noise (observation)

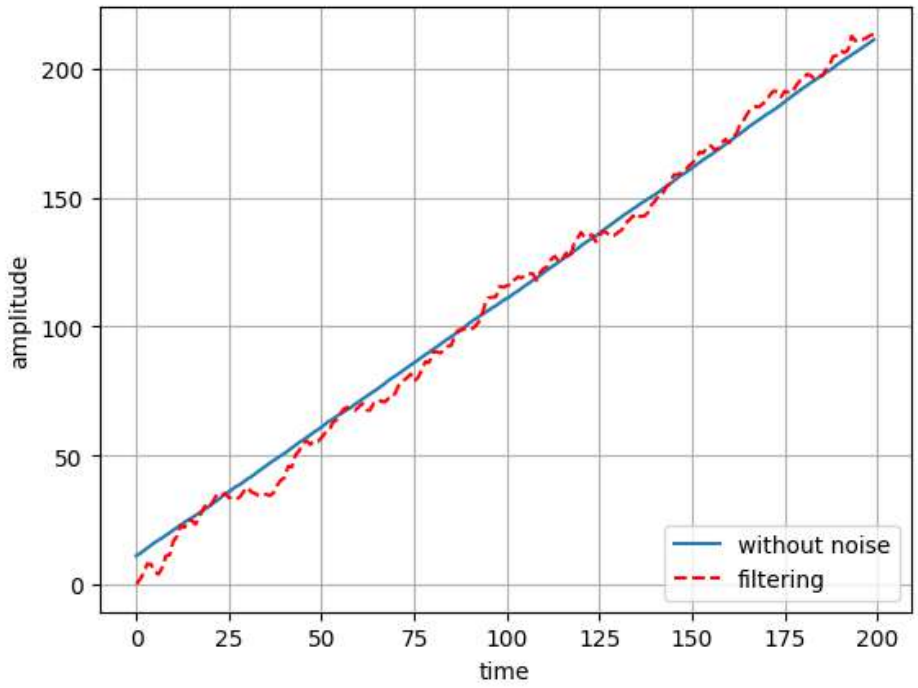

Figure 4: The original signal without noise and the observation estimate signal

10.Discussion

The advantage of using the proposed immune metaheuristic methods:

1. Automation of determination of Kalman filtering parameters A, σ_Q^2, σ_H^2, σ_R^2.
2. Immune metaheuristic methods, due to their stochastic nature, reduce the probability of convergence to a local extremum.
3. For immune metaheuristic methods, it is proposed to replace the Gaussian distribution with the Cauchy distribution, which is long-tailed, i.e. to reduce the probability of convergence to a local extremum.
4. According to Table 1, the modified hybrid immune algorithm method gives the best results in terms of the root mean square error.
5. According to Figure 3 and Figure 4, the original signal without noise and the filtered signal differ insignificantly, while there is a significant difference between the original signal without noise and the signal with noise.

Conclusions

1. A modified Kalman filtering method was developed that provides automation of parameter value determination and increases the speed and accuracy of Kalman filtering by using fewer parameters and identifying them based on immune metaheuristic methods.
2. A modified artificial immune network method was created that reduces the probability of convergence to a local extremum by using the Cauchy distribution and makes the proposed method more accurate than the existing one.
3. A modified hybrid immune algorithm method was developed, which, by using the Cauchy distribution, reduces the probability of convergence to a local extremum and makes the proposed method more accurate than the existing one.
4. Algorithms of immune metaheuristic methods for identifying Kalman filter parameters have been developed, which are intended for software implementation on GPU using CUDA technology, which increases the accuracy of Kalman filtering. The numerical studies conducted have confirmed the operability of the developed software and allow us to recommend it for practical use.
5. Further research prospects include the use of the proposed immune metaheuristic methods for various general-purpose and special-purpose intelligent systems, for example, for training neural networks.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Multi-agent WAF pentesting on the JADE platform

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Abstract

This article presents an approach to automated penetration testing using a distributed multi-agent system (MAS) based on the JADE platform. The proposed architecture includes four specialized agents that collaborate to dynamically bypass Web Application Firewalls (WAFs) and Intrusion Prevention Systems (IPS). The system enables the real-time generation of polymorphic payloads, reinforcement learning-based adaptation of attack strategies, and distributed deployment to reduce detection risks. Experimental validation confirms that this multi-agent approach enhances the efficiency of vulnerability detection through parallel execution, intelligent payload mutation, and reduced reliance on manual testing.

Keywords Keyword

[1]Multi-agent system, penetration test (pentest), JADE, Web Application Firewalls, security bypass, machine learning, attack automation

1. Introduction

Multi-agent systems (MAS) are widely used today to solve complex problems in distributed environments where autonomy, adaptability, and interaction between software components are required. They enable the creation of flexible architectures in which software agents perform individual tasks, exchange information, respond to environmental changes, and work together to achieve common goals. Due to their scalability, self-organization, and ability to perform tasks in parallel, multi-agent approaches are effectively applied in areas such as social process modelling, logistics, robotics, telecommunications, and — notably — in information security.

One of the promising areas for applying multi-agent systems is penetration testing (pentesting) — the process of simulating an attacker's actions to identify vulnerabilities in software systems.

In modern cybersecurity, pentesting plays a key role in detecting vulnerabilities in web applications, networks, and systems. It allows for the assessment of security effectiveness, identification of weak points, risk evaluation, testing of defence mechanisms, and the development of recommendations for their improvement.

Traditional penetration testing methods — including the use of security scanners (such as Burp Suite, Nessus, OpenVAS), code analysis, and common attack vectors like SQL injection (SQLi), cross-site scripting (XSS), and CSRF — require significant human resources and are often unable to adapt to dynamic defence mechanisms such as Web Application Firewalls (WAFs) and Intrusion Detection/Prevention Systems (IDS/IPS).

The problem is that modern protection systems, in particular WAF and IPS/IDS, are able to dynamically change their behaviour. This is due to the use of artificial intelligence and machine learning algorithms, which enhance the systems' ability to automatically respond to new types of attacks. Under such conditions, traditional penetration testing methods do not provide sufficient adaptability of simulated attacks to real-time changes in the configuration of defensive mechanisms.

The use of multi-agent architecture in pentesting opens up new opportunities for automation — in particular, the development of mechanisms capable of promptly reacting to changes in protection behaviour and outpacing it during scanning, query generation, and system response analysis.

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The aim of this article is to develop an approach to automated pentesting using a distributed multi-agent system (MAS) based on the JADE platform. This system enables real-time generation of adaptive attacks, bypassing WAF/IPS filters, and improving the efficiency of vulnerability detection through the parallel cooperation of agents.

The scientific novelty of the study lies in the development and implementation of an innovative approach to pentesting automation using multi-agent systems. The proposed solution enables effective vulnerability detection and circumvention of protection mechanisms such as WAF and IPS through the dynamic generation of polymorphic requests. This reduces reliance on human resources, accelerates the security testing process for web applications and systems, and improves both accuracy and adaptability of threat detection.

The practical significance of the proposed solution is in its applicability to real-world pentesting scenarios. The parallel operation of agents increases the speed of data collection and the accuracy of vulnerability detection. The system can be integrated into automated cybersecurity audit tools, utilized in educational environments, and embedded into software products with built-in self-testing capabilities.

2. Literature Review

The field of application of multi-agent systems (MAS) today includes solving complex problems in distributed environments that require autonomy, adaptability, and interaction between software components [1]. MAS enable the creation of flexible architectures in which software agents are assigned individual tasks but exchange information, respond to changes in the environment, and work together to achieve a common goal [2]. Due to their scalability, self-organization, and parallel execution capabilities, MAS are effectively applied in various domains, including the field of information security [3].

Modern security systems, particularly WAFs and IDS/IPS, play a significant role in protecting web applications. Their key tasks include defending against common attacks (e.g., SQL injection and XSS), real-time traffic monitoring, and adapting to new threats [4]. This adaptability is achieved through the use of artificial intelligence and machine learning techniques, which can automatically detect vulnerabilities [5].

An overview of the evolution of WAFs from signature-based to machine learning-based models is presented in [6]. The authors analyse the advantages and limitations of each approach, which is important for understanding current challenges in web application security.

The study [7] is dedicated to the use of machine learning techniques for detecting vulnerability scanning attacks in web applications. Although the classification results were promising, the models required further calibration to increase confidence in their predictions. The research highlights the potential for integrating machine learning with the AppSensor concept to improve intrusion detection and prevention systems at the application level.

The work [8] explores the application of artificial intelligence methods to enhance web application firewalls (WAFs) in detecting web attacks, particularly injection attacks. The authors analyse the effectiveness of various machine learning models, such as Naïve Bayes, k-nearest neighbors (k-NN), support vector machines (SVM), and linear regression, in classifying HTTP requests as malicious or safe. Using a synthetic dataset of over 100,000 requests, the study shows that these models can achieve malicious request detection accuracy ranging from 92% to 99%. The main goal of the study is to demonstrate the advantages of using AI in WAFs to improve attack detection accuracy and reduce false positives, which are common in traditional rule-based WAFs.

As stated in [5], modern WAFs are increasingly developed using artificial intelligence and machine learning methods, but there is also progress on the other side. The article [9] describes the WAF-A-MoLE tool, which employs mutation-based fuzzing to generate attacks targeting machine learning in WAFs. This demonstrates the potential of using adaptive attacks to test the robustness of defensive mechanisms.

In particular, the article [10] analyses in detail the methods of attack detection, including signature approaches, anomaly analysis and the use of machine learning, and compares the effectiveness of Snort and Suricata solutions. The proposed Intelligent Threat Detector (ITD) module for Suricata demonstrates the ability to adapt threat detection systems.

The article [11] discusses the extension of IDS/IPS capabilities using the Lua language, which allows creating dynamic settings to adapt to new attacks, which is useful for dynamically changing

payloads and obfuscating queries. The use of techniques such as URL encoding, Base64 encoding, or polymorphic SQLi/XSS helps to change the appearance of requests to bypass WAF and IDS/IPS filtering signatures.

Methods for bypassing security mechanisms are also discussed in [12], which analyses the use of SQLMap for automated obfuscation of SQL injections to avoid signature and heuristic detection of pentesting queries by security systems.

Article [13] proposes an approach to dynamically changing the behaviour of agents using expert systems and an extension language that improves their adaptability.

The authors of [14] analyze common web application vulnerabilities such as SQL injection, cross-site scripting (XSS), and others, and examine the tools and techniques used to detect and eliminate them. The article also discusses the stages of conducting VAPT (Vulnerability Assessment and Penetration Testing), including preparation, scanning, analysis, and the implementation of security measures. The main goal of the study is to emphasize the importance of regular web application security testing to prevent potential threats and ensure the protection of user data.

Study [15] presents a review of web application penetration testing methods, including a comparison of popular tools and a discussion of their effectiveness. The authors highlight the importance of automation in improving the efficiency of security testing.

The data gathering process in penetration testing involves automated or semi-automated collection of information about the target system. In [16], the automation of penetration testing is discussed through the use of attack planning models. The authors stress the importance of automation for effective vulnerability detection, including open port identification, configuration analysis, and vulnerability scanning. However, this process faces several challenges that affect the accuracy and efficiency of analysis.

Article [17] focuses on the integration of autonomous software agents into web services. The authors compare two popular platforms for multi-agent systems (MAS): JADE and SPADE. They explore how these platforms can be used to develop agents that interact through web services, which is a crucial aspect in distributed systems and service-oriented architectures (SOA). The paper discusses the fundamentals of web services, intelligent agents, and agent communication languages. The comparison between JADE and SPADE is based on the implementation of a simple MAS in JADE and its reimplementation in SPADE. This study helps to understand how different platforms support agent integration into modern web paradigms, particularly RESTful services and event-driven architectures.

Article [18] proposes a methodology for developing multi-agent systems using the JADE platform, covering analysis, design, and implementation. It provides a structured approach to building efficient agent-based systems.

Study [19] focuses on ensuring security in multi-agent systems built on the JADE platform. It addresses aspects such as authentication, encryption, and access control between agents.

Special attention should be paid to the problem of analysing large amounts of data and the use of distributed computing. Papers [5] and [6] investigate the principles of building multi-agent systems and their effectiveness in distributed computing. It is stated that the use of agents allows distributing the load between nodes, optimising queries and applying machine learning to classify data, and processing large amounts of data coming from different sources.

Paper [7] demonstrates the creation of tools for modelling complex systems based on AgentScript, which is usually associated with the AgentSheets platform, an environment for creating agent models and simulations, and assesses the prospects for using AgentScript to model multi-level systems. This was one of the authors' first attempts to choose a research tool, but the platform was not sufficiently adapted to solve the problem of pentesting.

In [8], an agent scanner was developed for penetration testing of web applications, including automated detection of XSS vulnerabilities. To develop the scanner agent, the MAS SPADE (Smart Python Agent Development Environment) platform was used, which provides the creation and organisation of interaction between agents (crawler and scanner). It runs on the Python programming language, which provides flexibility and speed thanks to libraries for web testing, such as Asyncio, OS, Httpx, Requests. The agent model was successfully tested on a vulnerable web resource, which allowed us to evaluate their effectiveness in real conditions and compare them with the advanced commercial analogue Burp Suite.

The effectiveness of the proposed approach is confirmed by the scanning results, which showed that the advantages of the scanning agent are its speed, ability to bypass defence mechanisms, and its cost. The multiagent system provided high flexibility in the process of creating a working model and

allowed automating some stages of pentesting, which significantly reduced the time required for security checks.

Despite the existence of developments (including the authors'), previous studies have not implemented a distributed multi-agent system for pentesting that combines automatic generation of bypass attacks, dynamic change of payloads in real time, and parallel interaction of agents for scanning, attacking, and analysing responses. The proposed research fills this gap by integrating JADE agents for intelligent data mining in the security testing process.

Furthermore, the integration of distributed agent-based systems can enhance real-time threat detection and response capabilities, improving the adaptability of pentesting tools in dynamic environments. These developments open new opportunities for optimizing the testing process by leveraging agent collaboration and real-time decision-making to bypass increasingly sophisticated security mechanisms.

3. Choice of Methods and Tools

In today's world of multi-agent systems, there are many platforms that allow you to create, develop and implement various agent models. Two of these platforms - JADE and SPADE - are among the most widely used in the field of multiagent systems development. JADE (Java Agent Development Framework) and SPADE (Smart Python Agent Development Environment) both provide powerful capabilities for creating agents and organising their interaction, but have different approaches and are focused on different goals.

SPADE, which is based on Python, is notable for its simplicity and flexibility, which makes it attractive for rapid development of medium-sized agent systems and for developers who prefer Python [24-25].

In contrast, JADE, built on the Java language, is known for its scalability, standards support, and agent mobility, making it ideal for large, complex, and distributed systems.

An overview of the JADE and SPADE platforms helps to define their capabilities, purpose, and application for different types of projects.

SPADE, developed for Python, supports the FIPA standard, simplifies the implementation of agents, communication between them, task synchronisation, and includes scalability. It is aimed at Python developers and is used to create agent systems in distributed environments, automation, and modelling.

JADE is a framework for the development of multi-agent systems in Java, which is based on the idea of supporting the FIPA standard. It provides agent mobility, includes tools for communication and task scheduling, and has a testing environment, and is designed to manage complex distributed systems where agents need to interact to achieve a common goal. For example, in large computer networks or for monitoring various systems; in decision support systems; for building intelligent information retrieval and processing systems (working with large amounts of data).

JADE is a powerful tool for developing agent-based systems in the cybersecurity industry due to its ability to detect anomalies in network traffic and respond to threats in real time. JADE is used to develop agent-based systems for monitoring and protecting information networks. Agent-based technologies allow you to create distribution systems to detect anomalies in network traffic and respond to potential threats. In IT, JADE is used to create automated agents that can interact with applications to test and detect errors, especially in complex distributed systems.

While SPADE excels in rapid development and ease of use for smaller systems, JADE is better suited for more sophisticated environments requiring high performance, scalability, and robust agent interactions. The choice between these two platforms often depends on the specific requirements of the project and the developer's preferences in programming language and system complexity.

JADE is superior to SPADE in scalability, supporting complex multi-agent systems, efficient processing of large amounts of data and distributed computing. It provides a higher level of interoperability with other platforms due to better FIPA support. Agent mobility in JADE is more flexible, and cross-platform compatibility allows you to work on Windows, Linux, and macOS without significant code changes.

The comparison presented in Table 1 looks at the main features, purpose, and application of both platforms to determine which one is better for certain types of projects and tasks [26-28].

Table 1
Comparison of JADE and SPADE platforms

	JADE	SPADE
General purpose	- a framework for developing complex, adaptive, distributed multi-agent systems where numerous agents interact to achieve a common goal	- a framework for the development of multi-agent systems, focused on medium and small-scale projects
Interoperability and standards	- supports the FIPA standard, provides high compatibility with other agent platforms. This allows you to create cross-platform agent systems that can interact with other	- supports the FIPA standard, integration with other systems is limited to Python capabilities (compatibility issues with large, multi-platform systems);
Mobility	-has built-in support for agent mobility, allowing agents to move between different computers and environments without losing context, useful for distributed and mobile applications	- includes scalability and supports the creation of agents that can move across different computers, supports mobility, but for medium-sized systems;
Support for multi-platform environments	- works with Windows, Linux and MacOS systems, allowing you to build cross-platform agent systems that operate in different environments without major code changes	- problems using the framework in environments other than those it was optimised for (library dependencies, version compatibility, network settings)
Interfaces and features -	-has interfaces for creating agents, communicating between them, and scheduling tasks; - includes a full-fledged environment for development, testing, and debugging; applies Java	- uses the Java programming language and supports a graphical interface for debugging and monitoring the work of agents; is focused on the use of the Python programming language;
Purpose	- to create complex, scalable agent systems where agents interact to achieve a common goal	- provides simple implementation of agents, communication between them and synchronisation of tasks
Applications	-development of intelligent agents for various industries - modelling and analysis of multifaceted systems involving a large number of agents;	- development of intelligent agents (Python) for various applications such as automation, distributed systems, robotics, smart cities

JADE is one of the most reliable platforms for developing distributed MAS, featuring built-in support for agent communication, container migration, and FIPA compliance. The environment offers powerful tools for the development, testing, and monitoring of agent-based systems, making it suitable for complex projects. It is a preferred choice due to its scalability and flexibility. The platform promotes research reproducibility, facilitates experiments with learning-based payload generation, and provides a solid foundation for the further development of intelligent systems.

4. Discussion: Using JADE to dynamically bypass WAFs when anomalies are detected

Modern Web Application Firewalls (WAFs) use various methods of attack filtering, including signature analysis, heuristics, and behavioural models, to provide effective protection against external threats. For effective security testing and threat analysis, a JADE-based agent system must adapt its payloads and change attack strategies to circumvent WAF defences.

The proposed automated pentesting system is implemented as a multi-agent system on the JADE platform, enabling parallel task execution, adaptation to the reactions of the protection system, and

learning based on feedback. The architecture involves the interaction of four main types of agents: Recon-Agent, Mutation-Agent, Attack-Agent, and Learning-Agent.

Recon-Agent is responsible for collecting initial information about the target system. It analyses server responses to various requests, attempts to detect active filters (such as XSS filters or WAF/IPS responses), and records key indicators that point to the type of filtering in use.

Mutation-Agent, based on data provided by the Recon-Agent, generates payload variants for testing the filters. This agent dynamically alters requests in order to bypass signature-based WAF filters by applying encoding techniques (URL, Hex), polymorphic XSS and SQL injections, as well as injecting invisible characters or modifying syntax. As a result, it produces a set of potentially evasive payloads tailored to the specific behaviour of the protection system.

Attack-Agent performs the mutated attacks against the web application, testing the effectiveness of the selected payloads. It logs response codes (403, 406, 500) and differences in request processing time. If protection mechanisms trigger, the agent records an error or lack of response; if the attack succeeds, the result is marked as successful and forwarded for further analysis. It interacts with the Mutation-Agent, sending feedback to refine the payloads accordingly.

The Learning-Agent analyses successful and unsuccessful bypass attempts, using reinforcement learning methods to adapt attacks in real time. This agent builds a database of effective attacks for specific types of WAFs, constantly improving the circumvention strategies.

Figure 1 illustrates the system architecture.

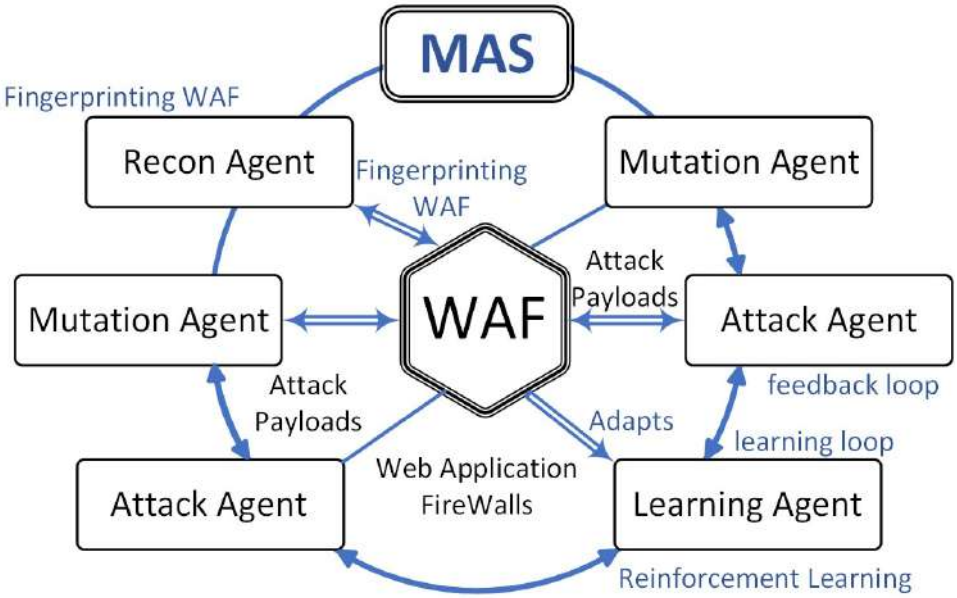

Figure 1: System Architecture

Dynamic adaptation and WAF evasion are achieved through coordinated interaction among agents: the Recon-Agent identifies active filters and protection constraints; the Mutation-Agent generates evasive payloads based on the detected characteristics; the Attack-Agent sends the requests to the target system; and the Learning-Agent analyzes server responses and adjusts attack strategies to further optimize the system's behavior.

Communication between agents is implemented using FIPA-compliant protocols supported by the JADE platform. The architecture is designed for scalability—allowing deployment either locally or as a distributed network of agents interacting via the JADE Remote Monitoring Agent (RMA).

Thus, the proposed architecture provides flexible adaptation to changes in protection mechanisms, automates the generation and testing of attacks, and significantly reduces the need for manual intervention during penetration testing stages.

4.1. Examples of dynamic WAF bypass

The attack process is illustrated below as part of penetration testing using the agents described above:

1) Recon-Agent. The first stage of the attack is to gather information about the website's security mechanisms.

Example: The Recon-Agent uses techniques to analyse HTTP headers, examine URL parameters, and study server behaviour (in particular, whether certain characters or patterns such as <script> are blocked). It can also perform WAF fingerprinting to identify a specific security solution (such as Cloudflare or ModSecurity).

Agent task: Determine how the website processes user input and what filtering methods or restrictions are applied.

2) Mutation-Agent. After collecting the information, Mutation-Agent generates new variants of malicious requests that can bypass the detected restrictions based on the data received from Recon-Agent.

Example: If Recon-Agent detects that a website blocks standard scripts, Mutation-Agent can modify requests using different coding methods (e.g., URL coding: %3Cscript%3Ealert(1)%3C%2Fscript%3E) or use polymorphic versions of XSS injections. You can also try inserting JavaScript events (e.g. onerror or onload) into HTML attributes (e.g. <img src='x' onerror='alert(1)'>).

Agent task: Generate new variants of malicious requests that are more likely to pass through WAF filters.

3) Attack-Agent. The Attack-Agent launches attacks by sending compiled payloads and then analyses the server responses.

Example: Attack-Agent sends generated payloads to a website, for example, with XSS code or SQL injection, checking whether these requests are executed and logging the response status code (e.g. 403, 406, 500). In addition, it measures the processing time of requests to assess for delays or anomalies that could indicate blocking attempts.

Agent's task: Determine whether attacks on a web application are successful by analysing server responses to different pingbacks.

4) Learning-Agent. This agent analyses successful and unsuccessful bypass attempts using reinforcement learning techniques to adapt attacks in real time.

Example: After the Attack-Agent receives responses from the server, the Learning-Agent evaluates which attack strategies were effective (e.g., which payloads were able to bypass the WAF). Based on this experience, the agent adapts attack strategies by changing the parameters of payloads or methods to respond to changes in the web application's security mechanisms (for example, if the WAF changes its rules after previous attacks).

The task of the fourth agent is to optimise and adapt attack strategies in real time to make them more effective based on new trials and errors.

The general process is that the Recon-Agent analyses the system to determine how the WAF works and how it filters requests. Based on this information, the Mutation-Agent generates new variants of malicious requests, adapting them to the detected limitations. The Attack-Agent then sends these requests to the server, analysing the responses to see if the WAF's defences can be bypassed. Based on the test results, the Learning-Agent optimises attack strategies, adapting them to changes in the defence mechanisms to increase the effectiveness of attacks. Thus, the entire process is a dynamic attack that constantly adapts based on the WAF's responses and the application of various circumvention strategies in real time.

4.2 Implementation of distribution in a multi-agent system.

The concept of distribution is realized through agents that operate independently while exchanging results and coordinating to achieve a common goal. To mitigate the risk of detection through IP-based filtering or regional restrictions, agents can be deployed on separate physical or virtual machines, including containers, strategically located in different countries.

For example, Recon-Agent can operate from different IP addresses so that data collection does not look like malicious requests from one location. Other agents, such as Mutation-Agent and Attack-Agent, can also run on separate servers to test different attack scenarios simultaneously. This allows for multi-functional attacks to be launched through different sources, reducing the likelihood of the entire system being blocked by the attacks.

Multiple Recon-Agents can run on different parts of the same website or on different websites to gather information about security mechanisms. They simultaneously test different pages, collecting metadata, HTTP headers, request parameters, and server responses from different points, which

allows them to gather more information about WAF settings. The results of the collected information are transferred to a centralised database that is used by other agents.

The Mutation-Agent can be run on multiple nodes simultaneously to generate different variants of payloads. This allows you to respond faster to different types of WAFs by generating paloads for different WAF configurations at the same time. For example, one agent generates payloads to bypass one type of protection, while another generates payloads for another type of protection. The payloads are then passed to the Attack-Agent for testing in parallel.

If the Attack-Agent is distributed among several nodes that send requests to websites from different parts of the world, it allows you to test different scenarios simultaneously and speeds up the attack process. Parallel testing on different servers increases the likelihood of a successful attack, as each server may have different approaches to blocking requests, which helps to identify vulnerabilities.

An example of a distributed multi-agent system for bypassing WAF, where specific server names, addresses, and access points can be used for each agent. The table also shows the names of the WAFs that the system will work with, as well as the stages of each agent's work (Table 2).

Table 2
Distributed multi-agent system for bypassing WAF

Agent/. Server name	IP- address	Access point / URL	type WAF
Recon-Agent (Server 1)	192.168.1.101	https://target1.com/	Cloudflare WAF
Recon-Agent (Server 2)	192.168.1.102	https://target2.com/	Imperva WAF
Mutation-Agent (MuS 1)	192.168.2.101	https://target1.com/search	Cloudflare WAF
Mutation-Agent (MuS 2)	192.168.2.102	https://target2.com/search	Imperva WAF
Attack-Agent (AtS 1)	192.168.3.101	https://target1.com/search? query =<script>alert(1)</script>	Cloudflare WAF
Attack-Agent (AtS 2)	192.168.3.102	https://target2.com/search? query =<script>alert(1)</script>	Imperva WAF
Learning-Agent (LeS 1)	192.168.4.101	https://target1.com/search	Cloudflare WAF
Learning-Agent (LeS 2)	192.168.4.102	https://target2.com/search	Imperva WAF

A Learning-Agent can work as a central agent or as distributed agents working in different locations to evaluate the effectiveness of attacks (distributed learning). They collect data on attack success from different locations, compare strategies, identify patterns, and optimise them to avoid WAF blocking. For example, one Learning-Agent L1 learns successful attacks from one access point, and the Learning-Agent L2 learns from another. This data is then transmitted to a central server and stored in a database for further correction of attack strategies.

The scheme of work is as follows.

Recon-Agent: Two servers (recon-server-01 and recon-server-02) run on different access points (on different websites, target1.com and target2.com). They scan and collect information about the security mechanisms used on these sites (for example, Cloudflare WAF on target1.com and Imperva WAF on target2.com).

Mutation-Agent: Based on the information received from the Recon-Agent, two servers (mutation-server-01 and mutation-server-02) generate different payloads to bypass specific WAFs (Cloudflare on target1.com and Imperva on target2.com). These servers may use techniques such as Base64 encoding, polymorphic XSS, or SQL injection.

Attack-Agent: The attack-servers -01 and -02 send payloads generated by the Mutation-Agent to target access points, such as target1.com and target2.com, to test the effectiveness of attacks against these sites. They record server responses (e.g., 403, 406, 500 codes) for further analysis.

Learning-Agent: The learning-server-01 and learning-server-02 servers collect data on attack successes and failures, analyse the results, and optimise strategies to bypass the WAF. For example, if a certain type of attack fails, the Learning-Agent changes the attack strategy and passes it to the Mutation-Agent to create new payloads.

Let's name the advantages of the proposed distributed multi-agent system:

Scalability: Due to the ability to run many agents simultaneously on different nodes, the system can easily scale to handle large volumes of traffic or to test on numerous websites simultaneously.

Minimising the risk of blocking: Distributed agents operating from different locations (e.g., different IP addresses or countries) reduce the likelihood that an attack will be detected and blocked due to increased activity from a single source.

Improved attack speed: Due to the parallel execution of all stages (data collection, payload generation, testing, optimisation), an attack can be carried out faster, which allows you to effectively bypass new and unusual security mechanisms.

Flexibility in adaptation: Distributed learning allows agents to quickly adapt their strategies based on changes in WAF behaviour or changes to web application settings.

Protection against detection: Distributed and parallel operation of agents in different locations helps reduce the likelihood that the system will detect centralised attacks and block the entire process by analysing traffic anomalies.

Thus, distribution adds flexibility, resilience, and scalability to a multi-agent system, allows you to bypass WAFs and reduce the risk of detecting attacks, increase the complexity (efficiency) of pentesting and attacking WAFs, while reducing the likelihood of detection and blocking.

5. Description of test scenarios and test results

The purpose of the test is to evaluate the effectiveness of a JADE-based agent system in dynamic WAF circumvention using different payload mutation methods. Table 3 and 4 describe the test scenarios for WAF traversal, including the test objective, traversal methods, and expected results.

The objective of the first test is to detect basic XSS filters. For this purpose, the character encoding method (Hex, URL) are used. It is expected that the system will not block the request and a response will be received successfully.

The second test aims to bypass the WAF's heuristic rules using polymorphic SQL queries. The expected result is the successful insertion of SQL code without being blocked.

The third test evaluates behavioural filtering. The split bypass technique is applied. An XSS attack is expected to be executed when assembling parts of the payload.

These scenarios allow for assessing the effectiveness of different techniques for bypassing security filters.

Overall, more than 100 attempts were made with different mutation combinations, and on average, about 60% of the attacks bypassed the protection. The success rate depended on both the filter type and the specific mutation implementation. In particular, split-based XSS attacks showed higher effectiveness compared to SQLi. The example provided in the table:

Test 1 was successful: URL encoding helped bypass the WAF.

Test 2 failed: SQLi was blocked, likely due to strict server analysis.

Test 3 was successful: The WAF could not reassemble the payload parts into a single attack.

Table 3
Description of the test scenarios

Test No.	Test Objective	WAF bypass method	Expected result
1	Detect basic XSS filters	Character encoding (Hex, URL)	Response without blocking
2	Bypassing heuristic WAF rules	Polymorphic SQLi queries	SQL injection without blocking
3	Behavioural filter analysis	Split bypass	XSS execution when collecting payload parts

Table 4
Test execution and results

Test No.	Inbound payload	Bypass method	Response status	WAF bypass
1	%3Cscript%3Ealert(1)%3C/script%3E	URL coding	200 OK	Successful
2	' OR 1=1-- -	Polymorphic SQLi	403 Forbidden	Not bypassed
3	<scr<script>ipt>alert(1)</scr<script>ipt>	Split bypass	200 OK	Successful

Testing showed that JADE agents effectively modify XSS payloads to bypass signature-based WAF analysis. SQLi requires more complex evasion techniques (e.g., time-based attacks). The results confirm the viability of using a multi-agent architecture for dynamic WAF protection bypass and demonstrate the potential for automating adaptive attacks.

Based on the above tests, we can formulate ideas for further improvement: integrating machine learning to predict WAF filters and automatically generating SQLi bypass mechanisms.

We use the above-described multi-agent system (MAS) on the JADE platform, where agents work together to dynamically bypass the WAF. An example of the Recon-Agent code is shown in Figure 2. The Recon-Agent analyses server headers, WAF filters, and obtains information about the target.

```
// Recon-Agent (WAF Analysis)
public class ReconAgent extends Agent {
  protected void setup() {
    System.out.println("Recon-Agent started");
    ACLMessage msg = new ACLMessage(ACLMessage.INFORM);
    msg.addReceiver(getAID("MutationAgent"));
    msg.setContent("WAF data received: possible filters active");
    send(msg);
  }
                                        }
```

Figure 2: ReconAgent code example

Figure 3 shows a Java implementation of the payload mutator (with support for the split approach and URL encoding) that performs random rearrangement of characters in the input string, applies partial URL encoding to individual characters, and generates a result in the form of a string that simulates the structure that could be used by a real XSS payload.

```
    * Generates mutated payload with random encoding and character permutation
    * and character permutation      */
   public static String mutatePayload(String payload) {
     List<String> parts = new ArrayList<>();
     for (char c : payload.toCharArray()) {          // payload splitting
       parts.add(String.valueOf(c));
     }
     Collections.shuffle(parts);                    // random permutation
     Random rand = new Random();
     List<String> encoded = new ArrayList<>();
     for (String s : parts) {                       // random encoding
       if (rand.nextBoolean()) {
         encoded.add(urlEncode(s));
       } else {
         encoded.add(s);
       }
     }
    // js-join format for split traversal (visual attack)
     return "[\"" + String.join("\",\"", encoded) + "\"].join(\"\")";
```

Figure 3: Mutation-Agent code snippet

The example provides a visual payload: it only simulates the attack structure but will not execute until it is used in an executable context (e.g., in eval(), innerHTML, or DOM injection).

From a WAF bypass perspective, split attacks are useful for analyzing the behavior of the protective mechanism because visual payloads can trigger false positives or reveal how the filter responds to fragmented signatures. Executable versions, on the other hand, allow testing the full effectiveness of the attack

Here are the results of a series of 100 test requests to the WAF bypass system (Fig. 4)

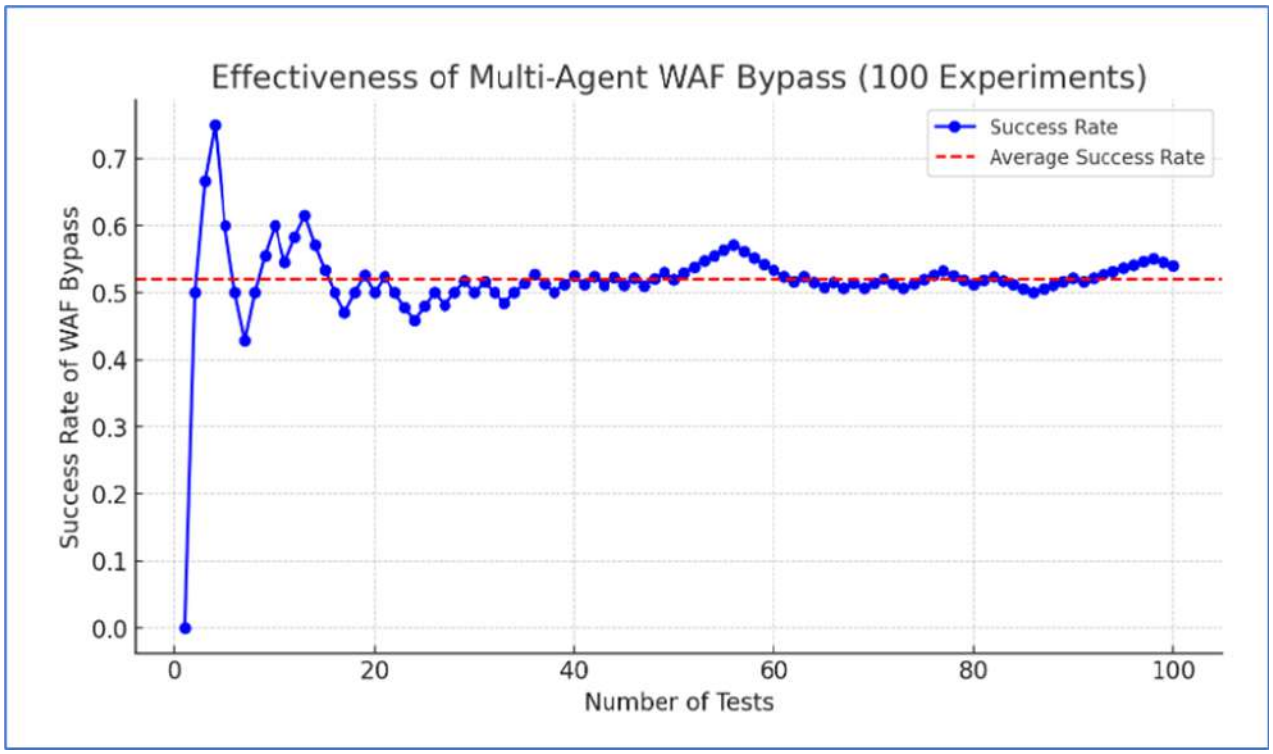

Figure 45 Testing Results

The graph shows the proportion of successful attacks against a WAF over 100 experiments. The blue line represents the cumulative percentage of successful attacks, and the red dashed line represents the average success rate, which is about 60%. This is the proportion of attacks that the WAF managed to bypass, which confirms the effectiveness of Mutation-Agent. However, the success rate of attacks varies during the training process, which leads to fluctuations. As the number of tests increases, the success rate becomes more stable.

6. Conclusions

This paper presents an innovative approach to automated penetration testing using a multi-agent system (MAS) based on the JADE platform. The proposed architecture enables effective task distribution among specialised agents, allowing for parallel scanning, adaptive attack generation, and real-time response analysis. Particular emphasis is placed on the Mutation-Agent, which dynamically alters payload structures to evade signature-based and heuristic detection methods of WAF and IPS systems.

Experimental evaluation demonstrated enhanced vulnerability detection performance compared to traditional methods, attributed to the high level of autonomy, adaptability, and self-organisation of agents. Reduced reliance on human resources, faster security assessment processes, and adaptation to dynamic defence mechanisms make the proposed system a promising tool for modern penetration testing.

The practical value of the solution lies in its potential integration into existing information security audit tools, as well as its applicability in training cybersecurity professionals.

Future research directions are outlined as follows. The current implementation focuses primarily on XSS and SQLi attack types. However, the modular and extensible system architecture allows for the integration of new agents to handle more complex attack classes, such as SSRF. While real-time adaptation to sophisticated attacks may increase computational overhead, this can be mitigated through agent-level parallelism and selective payload mutation.

JADE has been chosen for its reliability and comprehensive features, including inter-agent communication, container migration, scalability, FIPA-compliant messaging, and agent container management. These capabilities address most challenges related to message conflicts or agent interference. Nevertheless, managing false positives and false negatives remains a key area for future research. Additional enhancements may include improved load balancing strategies, expanded attack coverage, and the incorporation of machine learning models to predict defence system responses.

These advancements reflect the authors' long-term vision for developing an intelligent, modular, and scalable next-generation automated penetration testing platform.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Optimisation of Training Samples with KLE and Mutual Information

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Abstract

One of the key challenges in modern machine learning is reducing the dimensionality of the feature space in training samples while preserving essential information for classification and forecasting tasks. This study proposes a methodologically grounded approach that integrates the Kozachenko-Leonenko entropy (KLE) method with mutual information to enhance feature selection, thereby improving model accuracy and reducing computational complexity. A comparative analysis on the real-world dataset confirms the effectiveness of the proposed method in selecting informative features and improving classification performance.

Keywords

Kozachenko-Leonenko entropy (KLE) method, mutual information, machine learning, feature selection, dimensionality reduction, training sample

1. Introduction

The quality of machine learning models largely depends on the quality of training samples that are formed at the data preparation stage and directly affect the accuracy, generalisability and stability of the models. Effective data preparation involves data cleaning, transformation, selection of relevant features, and elimination of outliers. However, these processes are complex and require automation.

The concept of entropy is one of the most powerful mathematical tools that allows for such operations to be performed objectively and formally. Entropy methods allow to estimate the degree of uncertainty in training data, identify the most relevant features, and find optimal strategies for their processing.

The use of entropy for data processing is not a novel concept, but its relevance in modern machine learning tasks is only growing. One of the most well-known areas of its application is the discretisation of continuous features. For example, the Fayad-Irani method is based on entropy minimisation to determine the optimal partitioning thresholds, which allows obtaining compact and informative value intervals [1]. This technique is effective for improving trained models, which is confirmed by empirical studies [2, 3]. Such approaches allow not only to reduce the dimensionality of the feature space but also to improve the generalisation ability of the models.

Another important aspect is the selection of features based on entropy criteria. Methods such as information gain [4, 5] and Gini impurity [6-8] identify the extent to which each feature contributes to class recognition. This enables the elimination of redundant or insignificant features, thereby increasing the efficiency of classification algorithms. In particular, algorithms such as SelectKBest [9, 10] and Recursive Feature Elimination (RFE) [11, 12] are effectively used to select relevant features even in cases of large and unbalanced samples. Taking into account methods based on conditional and mutual information allows creating more flexible and adaptive feature selection strategies for further use in machine learning algorithms.

In addition to working with features, entropy is used to select the most informative training samples. In the context of active learning, one of the most common approaches is Entropy Sampling, where priority is given to samples for which the model has the highest uncertainty in predictions. This allows to significantly reduce the size of the training set without degrading the classification quality.

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Studies in computer vision and text analytics confirm the effectiveness of this strategy [13, 14]. It should also be noted that entropy analysis helps to assess the balance of classes in the training set. A low value of the entropy of the class distribution signals a significant imbalance, which can negatively affect the performance and accuracy of the model. Diagnostic criteria based on entropy help to identify such problems in time and apply appropriate corrective strategies, such as sample rebalancing or weighting.

Therefore, the use of entropy methods in the processing and analysis of training samples opens up wide opportunities to improve the efficiency of machine learning models. These approaches not only optimise the structure of the sample but also improve its information content, which directly affects the accuracy and stability of the built models.

2. Problem statement

One of the key challenges of modern machine learning is to reduce the dimensionality of the feature space without significant loss of information required to solve forecasting or classification tasks. The growing amount of data used in models leads to an increase in computational complexity, model overtraining, and a decrease in their generalisation ability. As a result, it is important to develop effective methods for selecting informative features and reducing the dimensionality of the space while retaining relevant information. Traditional approaches, such as principal component analysis (PCA) [15] or linear discriminant analysis (LDA) [16], are effective only under certain assumptions about the data distribution. However, in the case of complex, non-linear relationships between features, these methods may not be effective. An alternative is entropy-based methods for assessing the information content of features, which do not require any prior assumptions about the data distribution.

Therefore, the problem statement is to develop a methodologically sound approach based on entropy methods, which will improve the quality of training samples and, consequently, the accuracy of machine learning models.

3. Goal and objectives of the study

The purpose of this study is to analyse and justify the effectiveness of using entropy method for processing and analysing training samples in order to improve the quality of machine learning models. To achieve this goal, the following objectives are considered.

1. Analyse the capabilities of the Kozachenko-Leonenko entropy (KLE) method for assessing the informativeness of features in N-dimensional space.
2. Development of a combined approach using KLE and mutual information for feature selection to improve the quality of models and reduce the need for resources to solve classification or prediction problems.

The accomplishment of these objectives will contribute to the development of a methodological framework for machine learning and provide an effective approach to the preparation of training samples, which in turn will increase the accuracy and generalisation of models.

4. A combined approach using KLE and mutual information for feature selection

This section presents a novel approach to feature selection that combines KLE entropy and mutual information. By integrating these two methods, the proposed approach aims to improve the evaluation of feature relationships, decrease dimensionality of training sample and, as a result, enhance both classification accuracy and generalization performance. The first part of the section discusses the use of the KLE method in N-dimensional space for preparing the training sample, while the second part demonstrates how KLE and mutual information are combined to perform feature selection.

4.1. KLE method in N-dimensional space

The KLE method is an effective approach for estimating differential entropy in N-dimensional space. This nonparametric method, unlike its parametric counterparts, does not require any prior assumptions about the data distribution and works well even with complex, nonlinear distributions [17].

Let's assume that the task of training sample preparation involves the following.

1. Remove or reduce the influence of noisy data (outliers);
2. Select or transform a subset of features in such a way as to ensure the highest informativeness with respect to the output variable;
3. Ensure satisfactory accuracy of the machine learning model, even under conditions of incomplete information.

Denote the given dataset by $X=\{(x_i, y_i)\}, i=\overline{1,N}$, where $x_i \in R^N$ is a feature vector and y_i is the target variable ($y_i \in R$ for regression, $y_i \in \{C_1, C_2, \ldots, C_k\}$ for classification). The KLE method estimates the differential entropy of the feature space X, which is useful for analysing the informativeness of features and their relationship with the target variable Y.

The differential entropy of a random variable $X \in R^N$ is defined as

$$H(X)=-\int_{\mathbb{R}^N} f_X(x)\log f_X(x)\,dx, \tag{1}$$

where $f_X(x)$ is the probability density of the feature distribution.

The KLE algorithm for N-dimensional space is as follows. First, for each point x_i the distance to its k-th nearest neighbour is found (for example, with the Euclidean distance):

$$\rho_k(x_i)=\min_k\left\{\rho \vee \left|\{x_j \in X : \|x_j-x_i\| \le \rho\}\right| \ge k+1\right\}, \tag{2}$$

where $\rho_k(x_i)$is the radius containing k+1 points, including the point x_i itself; x_j is the point for which the k-th nearest neighbour is searched; $\|x_j-x_i\|$ is the distance between points x_i and x_j according to the selected distance metric; ρ is the value of the radius, which changes until the minimum value is found that satisfies the condition; k is the number of nearest neighbours that are taken into account.

The number of k nearest neighbours, which is taken into account when estimating the distribution of the noise component, can be calculated with the pseudocode from the Figure 1.

$k \leftarrow 1, k_{opt} \leftarrow 1, J_{min} \leftarrow J(1), Q = [J(1)]$
for $k = 2, \ldots, N$:
    calculate $J(k)$;
    $Q \leftarrow Q \cup \{J(k)\}$;
    if $|Q| > L$ **then** Q.pop_front();
    if $J(k) < J_{min}$ **then** $k_{opt} \leftarrow k, J_{min} \leftarrow J(k)$;
    if $\forall r \in Q: |r - J_{min}| < \varepsilon$ **then** break;
    if $J(Q_{first}) - J(Q_{last}) > -\varepsilon$ **then** break;
return k_{opt}.

Figure 1: Pseudocode for calculating the number of k nearest neighbours

The pseudocode in Figure 1 implements an adaptive method for finding the optimal value of parameter k, using a window of size L to track the dynamics of the evaluation function $J(k)$ changes and introducing a stopping condition based on the stability or deterioration of the function value.

The evaluation function $J(k)$ can be calculated with the equation

$$J(k)=\frac{1}{B}\sum_{b=1}^{B}\left[H_{KLE,k}(X_b)-\overline{H}_k\right]^2, \tag{3}$$

where $H_{KLE,k}(X_b)$ is the KLE entropy with fixed k (e.g., $k = 1$) on the sample X_b; $\overline{H}_k$ is the average KLE entropy with fixed k on the sample X_b; B is the number of samples (e.g., bootstrap samples or cross-validation samples); X_b is one of the B samples.

Next, the volume of a unit sphere in N-dimensional space is determined by the chosen norm. For example, for the Euclidean norm, the volume of a unit sphere

$$V_N = \frac{\pi^{\frac{N}{2}}}{\Gamma\left(\frac{N}{2}+1\right)}, \tag{4}$$

where $\Gamma(\cdot)$ is the gamma function.

The last step is to calculate the KLE-entropy estimate

$$H_{KLE} = \Psi(M) - \Psi(k) + \log(V_N) + \frac{N}{M}\sum_{i=1}^{M} \ln \rho_k(x_i) + \gamma, \tag{5}$$

where $\Psi(\cdot)$ is the digamma function, $\Psi(x+1) = \Psi(x) + \frac{1}{x}$; M is the number of sample points; $\gamma \approx 0.5772$ is the Euler-Mascheroni constant.

4.2. Combining KLE with mutual information

The mutual information is a powerful tool for detecting non-linear dependencies between features and the target variable, facilitating the construction of a dataset that is both balanced and information-rich [18]. Mutual Information measures the extent to which information about $X_b = \{(x_i, y_i)\}, i = \overline{1, N}$ helps to determine Y. If the values of X_b are conditionally independent, then mutual information will be

$$I(X_b, Y) = \sum_{j=1}^{N} I(x_{ij}, y_i), \tag{6}$$

provided that

$$p(x_{i1}, x_{i2}, \ldots, x_{i} \vee y_i) = \prod_{j=1}^{n} p(x_{ij} \vee y_i). \tag{7}$$

Accordingly, Mutual Information for x_i is defined as:

$$I(x_i \vee y_i) = \sum_{i=1}^{N} \sum_{y_i \in Y} p(x_i, y_i) \log \frac{p(x_i, y_i)}{p(x_i)\, p(y_i)}, \tag{8}$$

where $p(x_i, y_i)$ is the joint probability of events x_i and y_i; $p(x_i)$, $p(y_i)$ are the corresponding marginal probabilities of x_i and y_i.

Based on the integral Mutual Information scores given on the sample from the dataset X_b, it is possible to eliminate insignificant features, thus the sample for model training will be of the form

$$X_T = \{X_b \vee I(x_i \vee y_i) \geq \alpha\}, \tag{9}$$

where $\alpha -$ is the cut-off threshold.

This approach makes it possible to reduce the dimensionality of the feature space while maintaining a high level of relevance to the target variable.

If the model performance at the validation stage is insufficient, it is possible to add an algorithm for iteratively adjusting the α threshold or implementing the combined criterion $\phi(X_T)$, which aims to maximise the ratio by changing the α parameter and the structure of X_T:

$$\phi(X_T) = Score_{CV}(X_T) - \lambda |X_T|, \tag{10}$$

Where $Score_{CV}(X_T)$ is the average model quality score based on the cross-validation; $|X_T|$ is the number of selected features; $\lambda \geq 0$ is the penalty factor.

To sum up, the integration of KLE entropy and Mutual Information methods allows to significantly reduce the dimensionality of the initial feature set, while maintaining sufficient information potential for efficient model training. This increases not only the performance of machine learning algorithms, but also their stability and interpretability in real classification and regression tasks.

5. Comparative analysis of modelling results

One of the important stages of developing effective machine learning models is validation of the results on real data set, which allows to objectively assess the impact of preprocessing on the accuracy and stability of classification. To verify the quality of the proposed entropy methods, a comparative analysis of classification results using pre-processed and unprocessed training samples was applied.

5.1. Dataset

To evaluate the effectiveness of entropy-based methods for processing training samples to improve the quality of machine learning models, the Gas Sensor Array Low-Concentration dataset [19] is used. Table 1 shows a snapshot of the Gas Sensor Array Low-Concentration dataset. The full dataset contains 90 gas samples collected by 10 semiconductor sensors. The studied gases include ethanol, acetone, toluene, ethyl acetate, isopropanol and n-hexane at three concentrations: 50 ppb, 100 ppb and 200 ppb. For each gas and concentration combination, five samples were collected to provide a variety of data for modelling. Each sample consists of 9000 data points representing the sensors' response to the gas. Each sensor generates 900 data points, allowing for detailed analysis of their response to different gases and concentrations. The data was collected in three stages: baseline (5 minutes), gas injection (10 minutes), and purification (15 minutes) with a sampling rate of 1 Hz.

Table 1
Data: "Gas Sensor Array Low-Concentration"

Col1	Col2	Col3	Col4	Col5	Col6	Col7	...	Col9001	Col9002
ethanol	100ppb	0.3565	0.3345	0.3575	0.333	0.3565	...	3.9325	3.9315
ethanol	100ppb	0.3525	0.3305	0.3525	0.332	0.355	...	3.918	3.9205
ethanol	100ppb	0.355	0.3345	0.354	0.332	0.355	...	3.8825	3.8815
...	...	...	...	...	...	...	...	...	...
hexane	50ppb	0.3955	0.3805	0.394	0.3745	0.394	...	3.8995	3.8995

The presence of data for several types of gases, concentrations, and time phases (see Table 1) makes it possible to form a representative training set for building classification models in real-world conditions. Such a sample is optimal for testing the effectiveness of feature space reduction methods, in particular those based on entropy and mutual information.

5.2. Description of the experiments

The base machine learning model is the ensemble method Random Forest, where multiple independent decision trees are combined to enhance accuracy and stability. The implementation of machine learning algorithms and data analysis is conducted in Python, utilising libraries such as NumPy, pandas, matplotlib, scikit-learn, time, and psutil. These libraries support tasks including classification, dataset splitting (train_test_split), learning curve analysis, model training with RandomForestClassifier, performance evaluation metrics, t-SNE, PCA, and resource and execution time monitoring.

The dataset is initially divided into training and test sets, followed by model training based on a predefined target vector. To assess sensitivity to missing features, a mechanism is employed that retains only a fixed number of significant features, replacing the remaining ones with mean values computed from the training set. Classification quality is evaluated using accuracy metrics, ROC AUC, MAE, and MSE, while the model's performance dependency on training set size is examined through a learning curve analysis.

For feature space analysis and dimensionality reduction, t-SNE (a non-linear projection) and PCA (a linear projection onto principal components) are applied. In addition to classification performance, computational efficiency and resource consumption are assessed by measuring execution time and CPU load.

All computational experiments presented in the paper were conducted on a laptop equipped with an Intel Core i7-13620H processor (13th generation, 10 cores: 6 performance and 4 efficiency cores, base frequency 2.40 GHz) and 16 GB of RAM. The system operates on a 64-bit Windows operating

system with x64 architecture. Parallel computations were automatically handled through CPU multithreading using libraries such as scikit-learn, NumPy, and joblib, which support task parallelization via the n_jobs parameter. GPU acceleration was not employed, as the main computations involved tabular data processing and ensemble modeling (Random Forest), which are efficiently executed on modern CPUs.

5.3. Results of the experiments

The results of model testing presented in this section demonstrate a comparative analysis of the effectiveness of classification methods under conditions of incomplete input data and different approaches to feature preprocessing. Particular attention is paid to the quality of classification, stability of models, their ability to generalise, and computational efficiency.

Figure 2 a) (left) shows the effect of the available features on the classification accuracy in the absence of training set preprocessing (¬KLE). There is a gradual increase in classification accuracy with the number of available features, but this increase is non-linear and has some fluctuations. The initial accuracy values are low, and the maximum value does not reach one, which indicates a significant loss of information. These results indicate that even with an increase in available features, the classifier cannot achieve 'perfect' accuracy due to the influence of noisy or unrepresentative data. In Figure 2 b) (right), where the training set was pre-processed using the Kozachenko-Leonenko entropy (KLE) method, a much faster increase in classification accuracy is observed. With a small number of features, the accuracy values are almost the same as in the first graph, but after reaching a certain threshold (approximately at 7 features), the accuracy increases sharply and approaches one. This indicates a significant improvement in classification quality due to data preprocessing, which likely eliminated the influence of noisy or irrelevant features, making the model more robust to incomplete data.

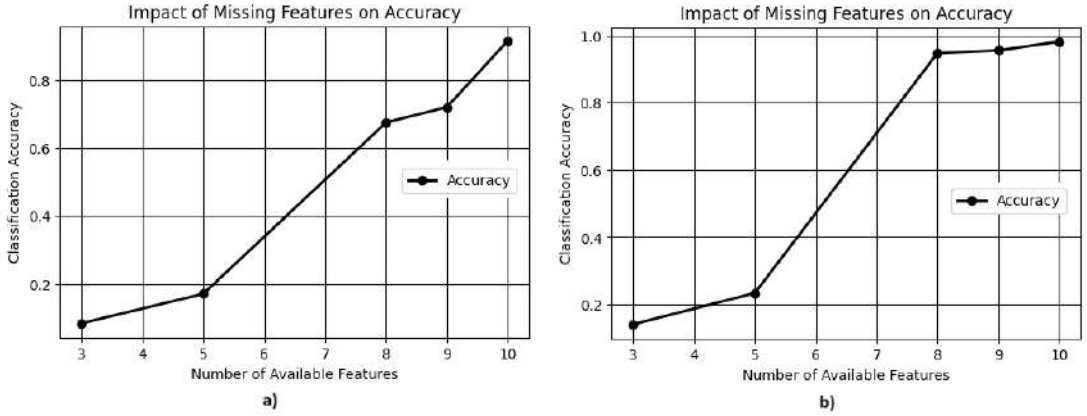

Figure 2: Incomplete data and classification accuracy

Figure 3 a) (left) shows that for the ¬KLE model, the training accuracy remains relatively stable as the training sample size increases, while the cross-validation accuracy gradually increases but remains below the training accuracy. This may indicate a certain level of overfitting, as the model demonstrates higher accuracy on training data than on cross-validation data. The difference between the two curves indicates the presence of noise and uneven distribution of information in the training sample. In Figure 3 b) (right), the KLE model shows a much better balance between training and cross-validation accuracy. Already with relatively small amounts of data, the model achieves high accuracy, and the difference between the two curves is much smaller, indicating better model generalisation and reduced overfitting. This confirms the effectiveness of pre-processing, which reduces the influence of irrelevant or noisy features and improves the quality of training.

In Figure 4 a) (left), there is significant chaos and high density of points for the t-SNE test of the ¬KLE model, indicating a weak structure in the data. The classes overlap significantly, which can make classification difficult. Such a distribution indicates the presence of noise and irrelevant information in the features, which can reduce the accuracy of the model and its ability to generalise patterns in the data. In Figure 4 b) (right), a more structured distribution of points is observed for the KLE model. Clusters are clearer, indicating improved differentiation between classes. This confirms the effectiveness of pre-processing in reducing noise and identifying hidden patterns in the data.

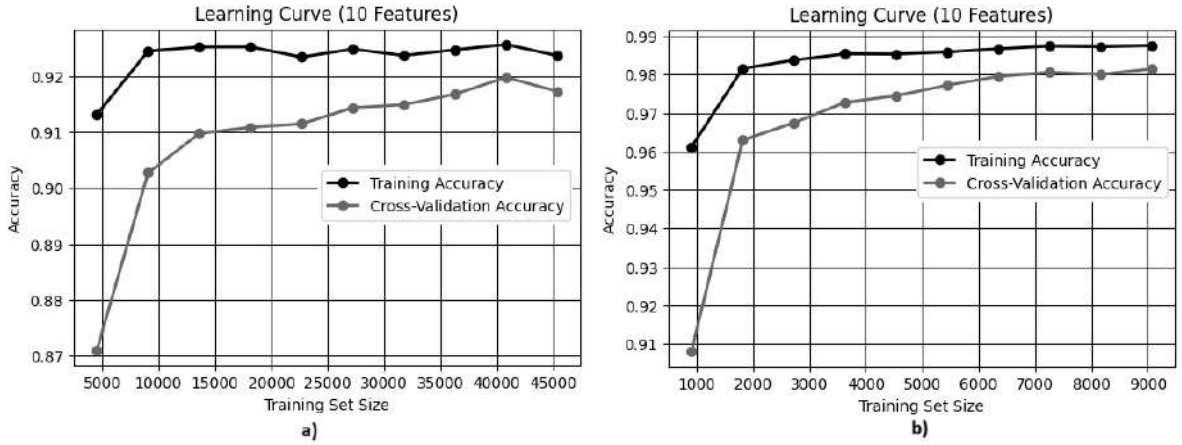

Figure 3: Comparison of learning curves of "¬KLE" and "KLE" methods

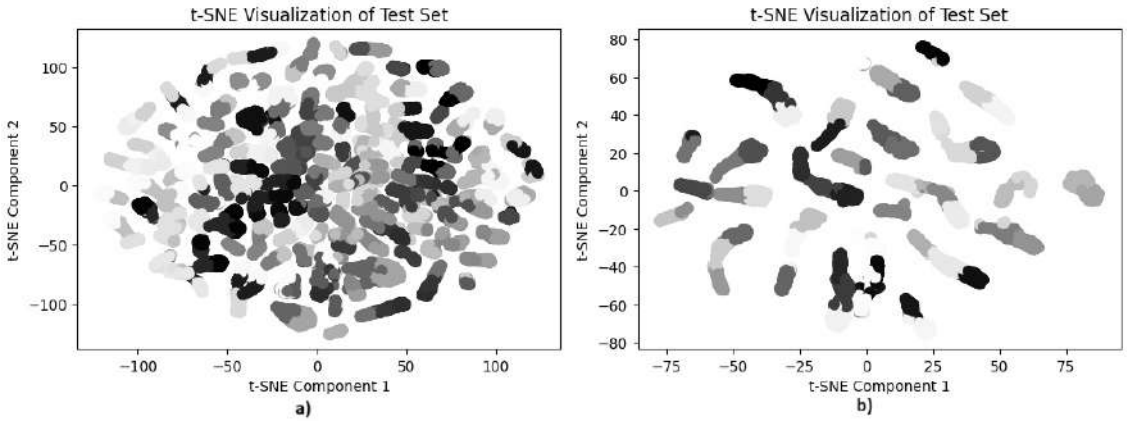

Figure 4: t-SNE analysis of the test set with different feature processing

Figure 5 a) (left) for the ¬KLE model shows that the data are unevenly distributed and have some clusters, but the structure remains blurred. The classes overlap to a large extent, which can make classification difficult, as there is no clear boundary between the groups. Such a distribution indicates that the original features contain a significant amount of noise or irrelevant information, which reduces the quality of model training. In Figure 5 b) (right), the KLE model shows a clearer separation between the groups, the data looks more clustered and has distinct directions in the principal component space. This indicates effective noise removal and improved differentiation between classes, which can improve classification accuracy.

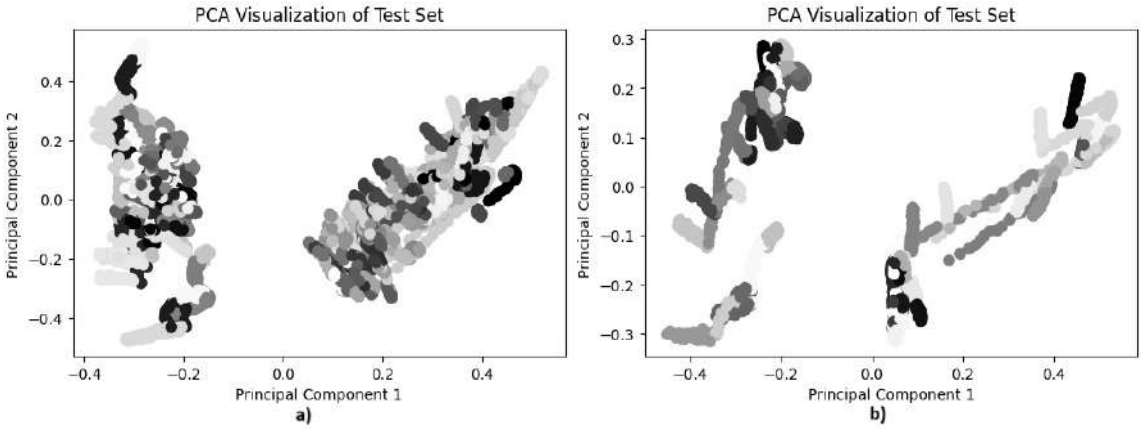

Figure 5: PCA analysis of the test set with different data processing

Figure 6 a) (top row) shows that without preprocessing, the prediction time and the CPU usage increases from 0.45 sec (3 features) to 0.67 sec (10 features), indicating the high computational complexity of the model. In Figure 6 b) (bottom row), after processing with the Kozachenko-Leonenko

entropy method, the prediction time increases only from 0.077 sec to 0.096 sec, while CPU Time stabilises at 0.094 sec after 6 features. This confirms the effectiveness of the processing in reducing computational costs and improving performance.

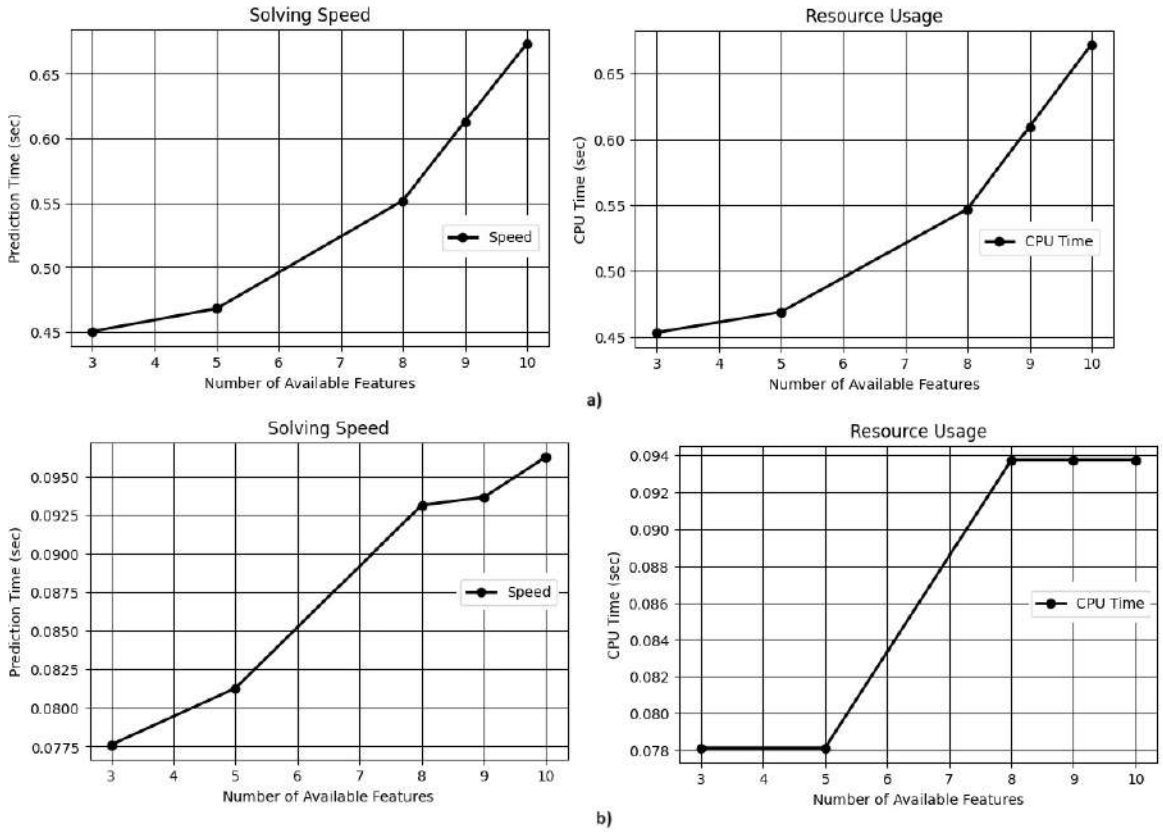

Figure 6: Dependence of performance and resources on training set pre-processing

Table 2 shows that without pre-processing (¬KLE), all metrics deteriorate sharply as the number of features decreases: AUC-ROC drops from 0.999 (10/10 features) to 0.747 (3/10 features), MAE and MSE increase significantly, and Log Loss increases from 0.525 to 5.427, indicating a loss of model stability. This indicates that without preprocessing, the model becomes very sensitive to a decrease in the number of features, which impairs its ability to generalise patterns. On the other hand, with KLE, the classification accuracy remains consistently high even with incomplete information. For example, the AUC-ROC changes less sharply (from 1.000 to 0.805), and the MSE and Log Loss remain at lower levels than in the case of ¬KLE. This shows that entropy processing improves model generalisability and reduces the impact of missing features, making the algorithm more robust to incomplete data.

Table 2
Quality metrics of models

Number of input parameters	AUC-ROC		MAE		MSE		Log Loss		Macro-F1	
	¬KLE*	KLE	¬KLE	KLE	¬KLE	KLE	¬KLE	KLE	¬KLE	KLE
10/10	0.999	1.000	0.486	0.029	14.35	0.05	0.525	0.097	0.91	0.98
9/10	0.997	0.999	1.589	0.282	40.16	8.46	1.038	0.407	0.69	0.95
8/10	0.996	0.999	2.180	0.637	53.80	23.88	1.421	0.776	0.64	0.94
5/10	0.847	0.899	11.118	7.641	244.37	157.74	4.827	7.058	0.11	0.14
3/10	0.747	0.805	12.877	13.915	302.93	427.91	5.427	12.562	0.05	0.06

** - Machine learning algorithm without using KLE for preparing the initial sample*

The results in Table 2 demonstrate that data preprocessing using KLE not only improves classification accuracy, but also ensures the stability of the metrics while reducing the amount of input

information. This approach is effective both in terms of model quality and computational performance.

6. Conclusion

The primary goal of this study was to develop and substantiate an effective method for optimization of training sample, based on entropy theory, combining the Kozachenko-Leonenko entropy (KLE) and mutual information. The declared objectives included analysing the potential of KLE in N-dimensional feature space and constructing a hybrid approach for feature selection to enhance model quality and reduce computational cost. The findings fully reflect the achievement of these objectives.

The proposed method offers a non-parametric evaluation of differential entropy, capable of detecting noise and selecting informative features without relying on prior distributional assumptions. The integration with mutual information enables identification of features most relevant to the target variable, contributing to the creation of a compact yet expressive feature space.

Empirical validation on the Gas Sensor Array Low-Concentration dataset confirmed the practical effectiveness of the method with the following results.

1. The AUC-ROC metric under preprocessing with KLE remained high even with partial data (1.000 with the full feature set; 0.805 with only 3 out of 10 features), whereas in the unprocessed baseline it dropped to 0.747.
2. The Mean Squared Error (MSE) remained low (ranging from 0.05 to 427.91 depending on the number of features) for the proposed method, indicating improved noise resilience.
3. The Macro-F1 score remained consistently higher (ranging from 0.98 to 0.06 for KLE vs. 0.91 to 0.05 for the baseline) under feature removal scenarios.
4. Prediction time decreased from 0.67 seconds (baseline) to 0.096 seconds (with KLE) for 10 features, demonstrating enhanced computational efficiency.
5. Visualisation techniques such as t-SNE and PCA further confirmed improved class separability and reduced noise.

The analysis shows that the use of KLE entropy allows for an objective assessment of the informativeness of features, reducing their number without losing relevance, which significantly increases the accuracy and stability of models. The use of mutual information in combination with KLE facilitates the selection of the most significant features, which minimises the influence of noise factors and allows optimising the feature space for training. The results also show a significant reduction in model overfitting and computational costs by removing redundant information.

Therefore, this research presents a theoretically grounded and empirically validated approach to entropy-based preprocessing. The alignment between the initially defined objectives and the achieved results has been demonstrated through both qualitative and quantitative analysis. This work provides a foundation for the further integration of entropy-driven techniques into advanced machine learning pipelines, particularly in domains characterised by complex or imbalanced datasets.

7. Directions for further research

The use of entropy criteria in combination with deep learning methods can significantly improve the quality of training samples, especially in high-dimensional spaces. In particular, a promising area is the adaptation of the KLE method to analyse the relationship between features in deep neural networks, which will not only reduce the feature space but also determine their informativeness in the context of multilevel data representations.

Special attention should be paid to the integration of entropy-based approaches with active learning methods, which will allow for dynamic sample adjustment in the process of model training. The use of strategies similar to Entropy Sampling will allow optimising the balance of classes and selecting the most informative examples for training. Further development of such approaches may include the creation of adaptive algorithms that combine estimates of differential entropy and mutual information to optimise the learning process in real time. This will not only reduce computational costs, but also improve the generalisation capability of the models, ensuring their stability even in circumstances of high variability in input data.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Thermal Image Super-Resolution via Lightweight Efficient Channel Attention Network

Andrii Didenko[1] and Andrii Oliinyk[1]

Abstract

Single Image Super-resolution (SISR) methods are actively developed with the help of advancements in Convolution Neural Networks (CNNs) and attention mechanisms. Following the progress in RGB SISR methods, thermal image super-resolution methods (TISR) are beginning to adopt and implement these advancements. Despite showing prominent results, modern state-of-the-art SISR methods often have a large number of parameters, leading to a significant computational overhead and memory consumption and making it difficult to run these methods in real-time or on edge devices. To address these problems, we propose a parameter-efficient TISR model named LECAN, which consists of a stack of efficient channel-spatial attention blocks (ECSAB). Specifically, the ECSAB combines Pixel Attention (PA) with the proposed Efficient Contrast-aware Channel Attention (ECCA) to extract both spatial and channel-wise features while maintaining a low parameter count. Meanwhile, the Attentive Feature Fusion (AFF) mechanism effectively combines information from all blocks, capturing both low-level and high-level features. The qualitative and quantitative results show that the proposed method achieves superior results among same-size models while preserving the texture and patterns of the thermal image with a small number of parameters.

Keywords

Image super-resolution, thermal image, deep learning, attention mechanism, lightweight network

1. Introduction

The ability of thermography to capture light information beyond the visible scope has made it in demand in many spheres. Unlike thermal cameras, RGB cameras often struggle to capture images in low-light and bad weather conditions, making them highly sensitive and dependent tools. Moreover, thermal images are also used as an additional source of information, enhancing the overall process of data analysis. These advancements have made thermography a preferable instrument in many fields, including medicine [1], UAVs [2], agriculture [3], etc.

On the other hand, due to the high cost and complexity of producing high-resolution thermal cameras, the output infrared image is often low-resolution. This constraint makes analyzing thermal data difficult, making it harder to distinguish small details in the image. This, in turn, leads to a decrease in the quality of data analysis. To overcome this issue, image super-resolution (ISR) techniques can be used, that are invariant of the camera hardware.

With the development of CNNs, ISR task can be accurately solved with the help of deep learning techniques. These methods rely on the convolution operation, which can effectively extract patterns and textures of different complexity. On the other hand, to achieve high performance, these methods stack a sufficient amount of layers, making the overall size of the model large. This disadvantage makes it hard to integrate these models on edge devices or use them in real-time.

Efficient ISR methods help to decrease the size of the model while keeping the overall performance high. On the other hand, the development of such methods remains difficult due to the complexity of accuracy-size trade-off.

In this paper, we propose a novel architecture called Lightweight Efficient Channel Attention Network (LECAN) that is based on a combination of channel and spatial attention mechanisms. To keep the number of parameters low, we propose a combination of Contrast-aware and Efficient Channel Attention mechanisms. This structure helps to accurately extract fine details at different frequency levels.

The main contribution of the paper is:

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- We propose a novel architecture called LECAN that consists its key components called Efficient Channel-Spatial Attention Blocks (ECSAB). The architecture of ECSAB allows to extraction spatial and channel features in parallel by dynamically recalibrating the importance of channels and pixels.
- We propose to use the Efficient Contrast-aware Channel Attention block (ECCA) for solving the TISR task. This idea combines the strength of contrast-aware feature extraction and the efficiency of ECA.
- The qualitative and quantitative results show that the proposed method demonstrates competitive results in different benchmarks with less number of parameters.

2. Related work

2.1. Image Super-Resolution methods

2.1.1. CNN-based

Image SR methods began rapid development since the CNNs became popular. SRCNN [4] was the first method to apply a CNN network to solve SR, consisting of 3 convolutional layers and becoming a state-of-the-art method at one time. However, 3 convolutional layers are not enough to learn a sufficient amount of patterns for reconstruction. The authors of VDSR [5] used 20 convolutional layers, showing significant improvements in results. Combining the advancements of residual learning [6] to increase the performance of very deep CNNs with Generative Adversarial Networks (GANs), the authors of SRGAN [7] proposed a GAN-based SR model to further boost the performance of SR methods. On the other hand, the training process of GAN-based is difficult due to hard convergence and mode collapse. To achieve better performance, the authors of EDSR [8] proposed to remove batch normalization in SrResNet [7] blocks. Despite the fact that the process of stacking layers can gradually improve the accuracy of SR models, it will eventually become inefficient to apply in real-world scenarios because of the large number of parameters. Addressing this problem, the authors of RCAN [9] proposed the use of the Channel Attention (CA) mechanism to adaptively enhance channel-wise features based on the interdependencies of the channels.

2.1.2. Efficient SR

To overcome the problem of considerable complexity of most state-of-the-art methods, efficient models can be used. These models try to minimize the overall complexity by removing unnecessary layers, reducing the number of parameters of basic building blocks, distilling large models, etc.

The authors of PAN [10] proposed a network with Pixel Attention (PA) mechanism, that aims to enhance spatial dependencies with fewer parameters. A^2N model [11] uses building blocks that consist of attention and non-attention branches weighted by a dynamic attention module, that helps to dynamically adjust the impact of each attention branch. IMDN [12] employs the channel-splitting strategy, in which one part of the channels is kept while the other part is passed on for further processing. This strategy allows to improve the performance while reducing the number of parameters. The authors of RFDN [13] successfully improved the idea behind IMDN by enhancing channel-splitting operation and reducing the number of parameters in convolutional layers. BSRN [14] further improves channel splitting idea

Although efficient models are able to produce an upscaled image quickly and with low computational costs, the quality of the output image remains low compared to the original image. This trade-off emphasizes the need to develop efficient models that can process images with high accuracy while remaining small in size.

2.2. Attention mechanism

Inspired by human attention, the attention mechanism in deep learning helps the model focus more on important parts of the input data. The Squeeze-and-Excitation (SE) [15] block was proposed to enhance features in channel dimension by assigning weights to each channel. CBAM [16] further expands this idea by assigning weights not only in the channels but also in the spatial dimensions. The

Efficient Channel Attention (ECA) is an improvement of the SE block that uses a one-dimensional convolutional block to reduce the model complexity. The self-attention mechanism that is used in Vision Transformers [18] also inspired the development of transformer-based models for low-level vision tasks. SwinIR [18] adopted the Swin Transformer [20] as a baseline by creating a Residual Swin Transformer Block with a convolutional layer and long residual connection. IPT [21] also applied ViT-based architecture and introduced multi-task pretraining for low-level vision. HAT [22] combines channel attention and window-based attention to enhance performance by activating more input pixels.

In this work, we endeavor to enhance the ISR model with the strength of the attention mechanism, while keeping the model efficient at the same time.

2.3. Thermal Image Super-Resolution

Due to the domain specificity of RGB and infrared images, which include visual and contextual differences, directly applying SR methods developed and trained for RGB images on infrared images may not be beneficial. Therefore, there is a need to design and train models directly for the TISR task.

The authors of the PSRGAN [23] proposed to use GAN-based model along with multistage transfer learning for solving TISR task. TherISuRNet [24] method consists of several residual blocks for extracting features and different frequency levels. The authors of MPRANet [25] proposed residual- and attention-based network with convolution of different kernel sizes. ChaSNet [26] uses channel-splitting technique to improve feature extraction. LISN [27] also uses a channel-splitting idea to reduce the number of parameters. LDANet [28] uses blocks with attention and non-attention branches weighted by dynamic attention modules.

Despite noticeable results in TISR, this area is still under-researched compared to other low-level vision tasks. This supports the need to develop robust methods directly for solving TISR task.

3. Method

This section describes the architecture of the building blocks and the overall proposed network for thermal image SISR, as well as the motivation for their implementation and usage.

3.1. Network Architecture

The architecture of the proposed networks (Figure 1) follows the extended standard structure for the SR models: shallow feature extractor (SFE), deep feature extractor (DFE), feature fusion (FF), and image reconstruction (IR, upsampling).

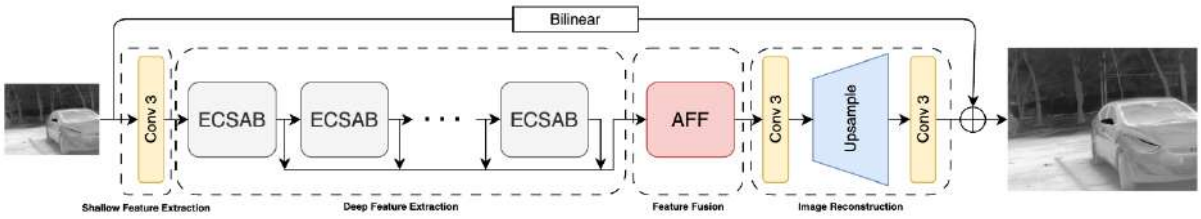

Figure 1: The architecture of the proposed method

The SFE is represented by a single convolutional layer with a kernel size of 3×3. Mathematically, the SFE is represented as follows (1):

$$x_{SFE} = f_{SFE}(I_{LR}), \tag{1}$$

where x_{SFE}– output features from SFE module;

I_{LR} – low-resolution image;

f_{SFE} – the function of the SFE module.

After shallow features are extracted, the output from the SFE module is then processed by the DFE module. The DFE module is the main part of the network which is responsible for extracting high-level features and complex patterns that might be useful for ISR. The DFE module consists of a stack of Efficient Channel-Spatial Attention Blocks (ECSAB), which will be explained in Section 3.2. The

output of the DFE module is the stack of outputs of each ECSAB module that is then processed by the AFF module. Mathematically, the DFE is represented as follows (2):

$$x_{DFE}=f_{DFE}(x_{SFE})=\left\{f_{B_1}(x_{SFE});f_{B_2}(f_{B_1}(x_{SFE}));\ldots;f_{B_N}(f_{B_{N-1}}(\ldots f_{B_1}(x_{SFE})\ldots))\right\}, \quad (2)$$

where x_{DFE}– outputs from DFE module;

f_{B_N} – the function of *N-th* ECSAB block.

The stacked outputs from the DFE module are then processed by the FF module to accurately fuse and extract the interdependencies between the output channels of each ECSAB block and the spatial features of the fused results. The FF module is represented by the AFF block, which is described in Section 3.3. Mathematically, the output of the FF module is expressed as follows (3):

$$x_{FF}=f_{FF}(f_{DFE}(f_{SFE}(I_{LR}))), \quad (3)$$

where x_{FF} – output features from FF module;

f_{FF}– the function of the FF module.

Finally, the IR module reconstructs the high-resolution image by upscaling it with the desired factor. Figure 2 shows the IR block. The IR module consists of one IR block if upscaling factor is 2 and two IR block if upscaling factor is 4.

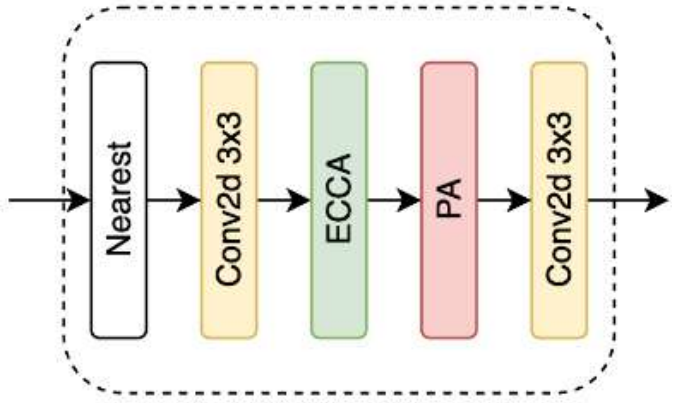

Figure 2: Image Reconstruction Block

IR block can be represented mathematically as follows (4):

$$x_{IR}=Conv(PA(ECCA(Conv(NN(x_{FF}))))), \quad (4)$$

where x_{IR} – output from IR module;

NN – nearest neighbor interpolation.

The overall mathematical formula for ISR is the following (5):

$$I_{SR}=f_{IR}(f_{FF}(f_{DFE}(f_{SFE}(I_{LR}))))+B(I_{LR}), \quad (5)$$

where I_{SR} – output upscaled image;

f_{IR} – the function of the IR module;

B – bilinear interpolation.

3.2. Efficient Contrast-aware Channel Attention Block

Simply combining the strength of the ECA [17] and CCA [12], we propose the ECCA block as part of the TISR method. First, the ECCA inherits parameter efficiency from the ECA block. Secondly, the contrast-aware part from CCA introduces a better refinement of textures and edges, allowing the model to capture information from low-, medium-, and high-level features. Following the original paper, the contrast-aware operation is the summation of each channel's standard deviation and mean. Figure 3 shows the structures of spatial-based attention (PA) and channel-based attention (including the proposed ECCA).

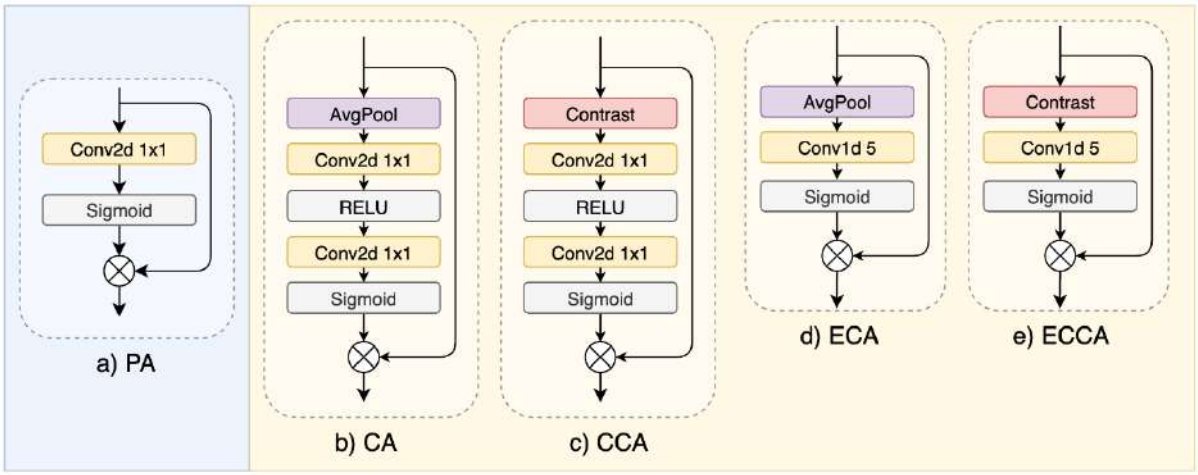

Figure 3:The visualization of attention mechanisms: a – Pixel Attention (PA), b – Channel Attention (CA), c – Contrast-aware Channel Attention (CCA), d – Efficient Channel Attention (ECA), e – Efficient Contrast-aware Channel Attention (ECCA).

Mathematically, ECCA can be expressed as follows (6):

$$x_{ECCA} = Sigmoid\left(Conv1d\left(mean_c\left(x_{in}\right) + std_c\left(x_{in}\right)\right)\right), \tag{6}$$

where x_{ECCA} – output from ECCA block;
x_{in} – input to the ECCA block;
$mean_c$ – per channel mean;
std_c – per channel standard deviation

3.3. Efficient Channel-Spatial Attention Block

The key component of the proposed method is the ECSA block and its combination of channel-wise and pixel-wise attention mechanisms. Specifically, this combination of two attention mechanisms allows the model to simultaneously focus on reweighting the feature maps along the channel dimension with the ECCA and emphasize the importance of individual pixels within the feature maps with the PA. Consequently, the network is able to leverage complementary information is across both spatial and channel dimensions. The parallel structure of applying attention mechanisms to the input features ensures independent behavior of extracting spatial and channel-wise dependencies with a further combination of the feature maps. Residual connections allow the preservation of input features' information for further layers. Figure 4 shows the architecture of the ECSA block.

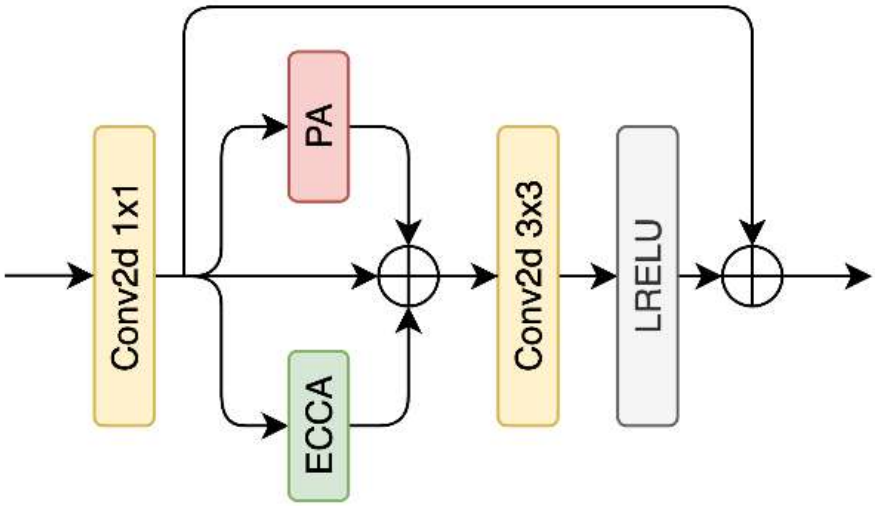

Figure 4: Architecture of the ECSA block

3.4. Attentive Feature Fusion

The AFF block serves as a additional part of the proposed model and its main goal is to efficiently fuse output features from different detailization levels. To do this, outputs from each ECSA block are concatenated along the channel dimension. Then, concatenated channels are processed with an ECCA block to extract dependencies across all blocks channel-wise. This operation allows the model to attend more to important information that might be spread along channels of different blocks, efficiently combining low-level and high-level features. Then, to reduce the number of parameters, the point-wise convolution is applied. In the end, the PA block is used to further process spatial information. In general, this module is based on the assumption that different levels of deep feature extraction might carry some portion of useful features and the attentive combination of features might improve the selection of this information. Figure 5 shows the architecture of the FFA block.

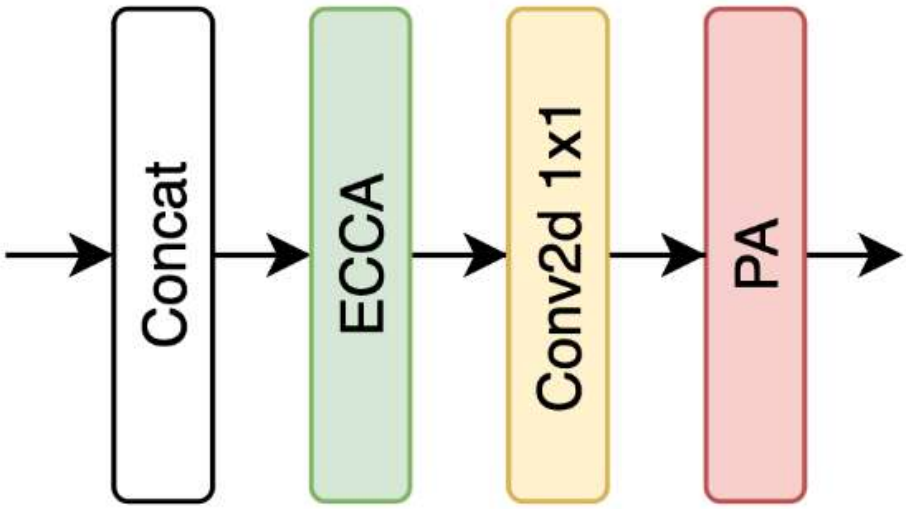

Figure 5: The architecture of the FFA block

4. Experimental analysis

The training setup for all models was the same to exclude the dependency of training parameters. AdamW [29] was used as an optimizer. The learning rate was set to 2e-4 with a MiltuStepLR scheduler that multiplies the learning rate by 0.5 at the following milestones: 50k, 65k, 80k, and 90k. The total number of iterations was set to 100k. During training, a patch of size 256×256 was randomly cropped from the HR image along with the corresponding patch from the LR image. The batch size during training was set to 8. Horizontal and vertical flips were used as data augmentation techniques, as well as random JPG compression with quality varying from 0.9 to 1. RSNR and SSIM were used as evaluation metrics. The experiments were conducted with PyTorch framework.

4.1. Training and testing datasets

For training, we used the Challenge dataset [30]. This dataset consists of thermal images of three different resolutions: LR Domo, MR Axis, and HR FLIR. To create a training set for this task, we downsampled HR FLIR thermal images by the scales of 2 and 4. The resulting dataset contains 951 images for training and 50 images for validation.

For testing, we used a recent Challenge dataset (Challenge 2) [30]. This dataset contains 1000 images, where 900 images are provided for training and validation, while the other 100 images are used to evaluate entries for the challenge (ground-truth is hidden). To create a testing set, 900 GT images were downsampled by scales of 2 and 4.

We also used CVC-09: FIR Sequence Pedestrian Dataset [31] by randomly selecting 1000 GT images and downsampling them by scales of 2 and 4.

4.2. Ablation study

We conducted the ablation study to examine the effect of different attention mechanisms in the network. Specifically, we trained 4 models with CA, ECA, CCA, and ECCA blocks in the architecture. The results of the ablation study on Channel Attention type are shown in Table 1.

Table 1
The results of the ablation study on Channel Attention type. The top values are highlighted in red and blue respectively

Attention type	N Params (k)	PSNR (dB)	SSIM
CA	399	32,5775	0,9294
ECA	344	32,563	0,9292
CCA	399	32,5836	0,9296
ECCA	344	32,5894	0,9296

The results show that the contrast-aware part of the Channel Attention can improve the performance, while the usage of parameter-efficient Channel Attention reduces overall model complexity, keeping model's accuracy high.

4.3. Quantitative evaluation

We compared our proposed model with several state-of-the-art methods: SRCNN [4], BSRN [14], PAN [10], RFDN [13], A2N [11], and IMDN [12]. The quantitative evaluation shows that the proposed method achieves competitive results while remaining relatively small compared to other models. Tables 2-5 present quantitative results for each method, as well as the size of each model.

Table 2
The quantitative results on the Challenge 2 dataset with a scaling factor of 4. The top values are highlighted in red and blue respectively

Model	N Params (k)	PSNR (dB)	SSIM
SRCNN	8	31,0928	0,8959
BSRN	333	32,4592	0,9261
PAN	271	32,4990	0,9279
RFDN	530	32,5271	0,9276
A2N	1046	32,5683	0,9289
IMDN	696	32,649	0,9292
LECAN (proposed)	344	32,5894	0,9296

Table 3
The quantitative results on the Challenge 2 dataset with a scaling factor of 2. The top values are highlighted in red and blue respectively

Model	N Params (k)	PSNR (dB)	SSIM
SRCNN	8	41,6601	0,9746
BSRN	327	43,4645	0,9872
PAN	260	43,4757	0,9873
RFDN	524	43,3422	0,9867
A2N	1035	43,2968	0,9862
IMDN	687	43,5564	0,9867
LECAN (proposed)	336	43,5997	0,9874

Table 4
The quantitative results on the CVC-09 dataset with a scaling factor of 4. The top values are highlighted in red and blue respectively

Model	N Params (k)	PSNR (dB)	SSIM
SRCNN	8	37,4622	0,9075
BSRN	333	37,9992	0,9129
PAN	271	38,0288	0,9130
RFDN	530	38,0285	0,9129
A2N	1046	38,0571	0,9133
IMDN	696	38,0743	0,9135
LECAN (proposed)	344	38,0670	0,9136

Table 5
The quantitative results on the CVC-09 dataset with a scaling factor of 2. The top values are highlighted in red and blue respectively

Model	N Params (k)	PSNR (dB)	SSIM
SRCNN	8	41,2614	0,9418
BSRN	327	41,9301	0,9501
PAN	260	41,8375	0,9484
RFDN	524	41,7690	0,9474
A2N	1035	41,7778	0,9477
IMDN	687	41,7091	0,9466
LECAN (proposed)	336	41,8790	0,9491

4.4. Qualitative evaluation

The quantitative results show that the proposed method is able to reconstruct different patterns and textures of thermal images. The proposed model can Figures 6-9 present a qualitative analysis of LECAN comparing to state-of-the-art methods.

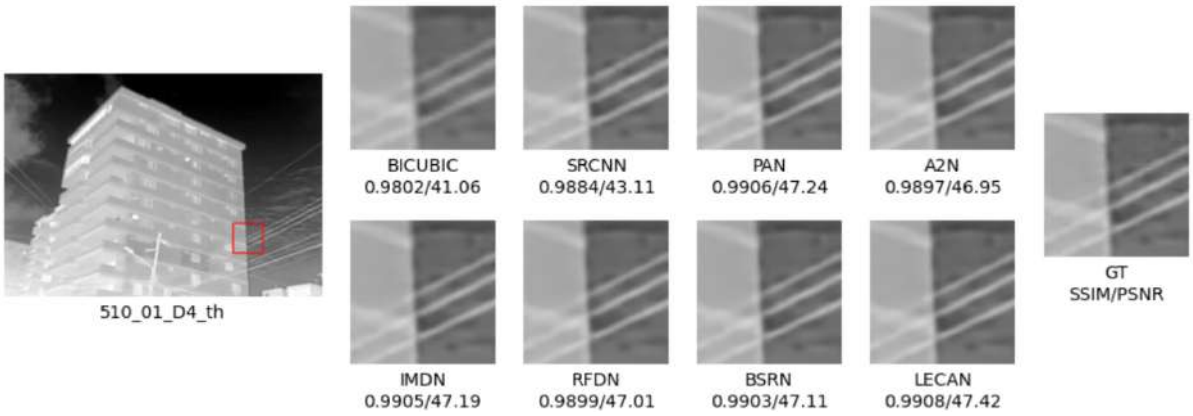

Figure 6: Qualitative results on the Challenge 2 dataset with a scaling factor of 2

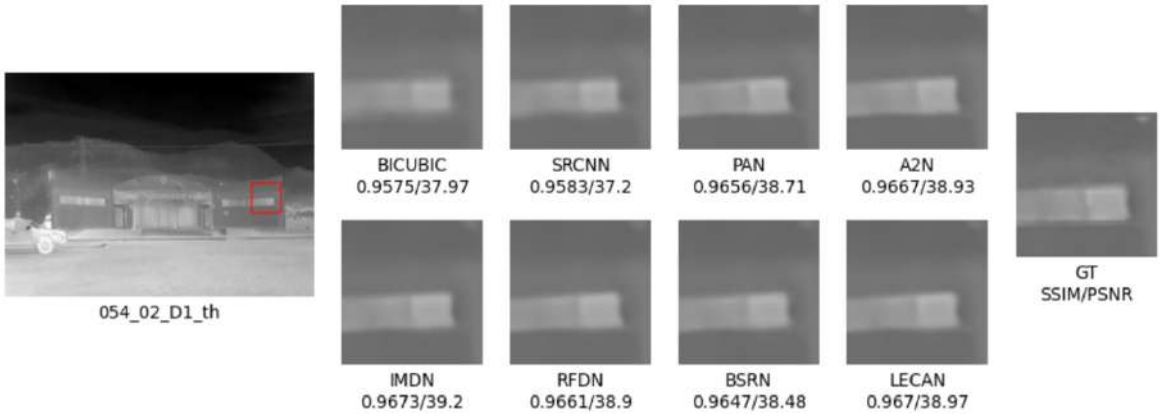

Figure 7: Qualitative results on the Challenge 2 dataset with a scaling factor of 4

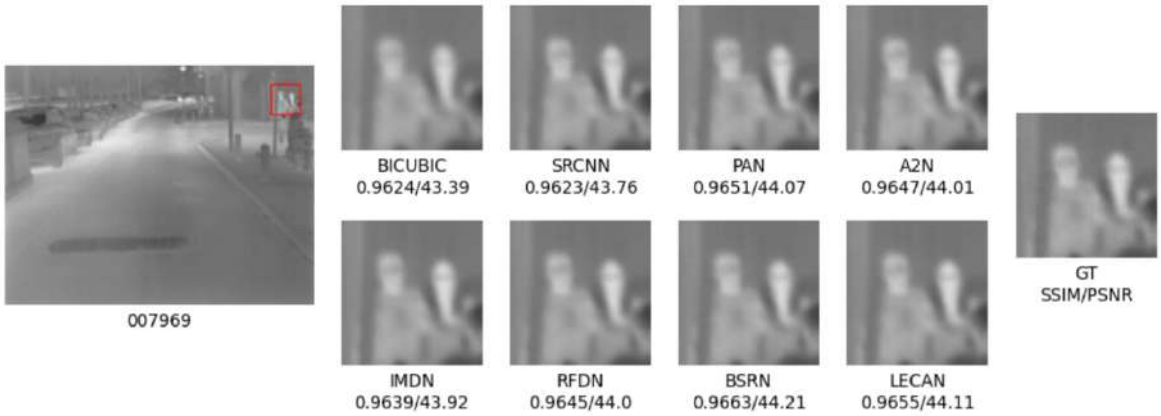

Figure 8: Qualitative results on the CVC-09 dataset with a scaling factor of 2

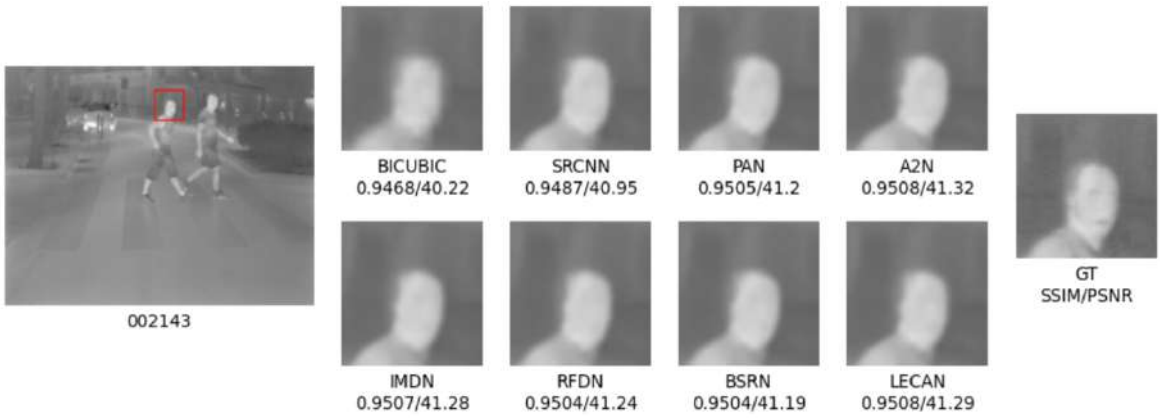

Figure 9: Qualitative results on the CVC-09 dataset with a scaling factor of 4

4.5. Inference speed evaluation

Inference evaluations were conducted on a server CPU AMD EPYC 7R32. The input image size is 256x256, and an average time of 10 runs was chosen. Table 6 lists the inference speed results in ms and the number of Floating Point Operations (FLOPs). The results show good trade-off between accuracy and inference speed.

Table 6
The quantitative inference results

Model	N Params (k)	Time (ms)	FLOPs (G)
SRCNN	8	118	4,26
BSRN	327	748	40,8
PAN	260	371	40
RFDN	524	418	68,47
A2N	1035	921	140,7
IMDN	687	433	89.8
LECAN (proposed)	336	559	48.6

5. Conclusion

In this paper, we propose LECAN for solving the TISR task. The proposed model consists of four main parts: shallow feature extraction, deep feature extraction, attentive feature fusion, and image reconstruction. The deep feature extraction consists of several ECSAB blocks. The ECSAB block efficiently combines channel and spatial attention mechanisms, where channel attention is represented by the Efficient Contrast-aware Channel Attention (ECCA) block, and spatial attention is represented by the Pixel Attention (PA) block. The combination of Contrast-aware and Efficient Channel Attention mechanisms allows to reduce the number of parameters and enhances the overall performance of the model. The qualitative and quantitative comparisons show that the proposed method demonstrates competitive results while maintaining a low parameter count. Further work can be aimed to improve the extraction of more complex features by enhancing attention mechanisms.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Trans-CAMNet: A Transformer-Based Grad-CAM Network for Lung Disease Classification

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Abstract

Accurate medical imaging analysis has become crucial in diagnosing and managing pulmonary diseases, especially considering the global prevalence of respiratory disorders. Chest X-ray classification has become one of the most effective diagnostic approaches in diagnosing pulmonary diseases and is valuable in offering clinicians a fast, noninvasive diagnostic solution. However, classifying thoracic abnormalities is challenging because of the variability of the pathological patterns and the lack of large annotated medical image datasets. To tackle these challenges, in this study, we introduce a novel approach that integrates fine-tuned deep learning-based frameworks, including CNNs and transformers. Further, to address the issues associated with deep learning models as black boxes, we employ the Grad-CAM as an interpretability technique to enhance clinical decision-making. It displays the areas that significantly contribute to the model's prediction of the lung regions. The proposed Trans-CAMNet framework, evaluated using the publicly available COVID-19 radiography dataset, achieves an accuracy of 98.33%, out-competing the traditional CNN architectures. These results highlight the possibility of transformer-based architectures in medical imaging tasks, with better classification accuracy and interpretability. These results provide a strong rationale for combining sophisticated deep learning architectures and interpretability methods to meet diagnostic performance and explainability in medical image analysis, especially for challenging pulmonary diseases.

Keywords
CNN, COVID-19, Grad-CAM, Deep Learning, Pulmonary Diseases

1. Introduction

The development of medical imaging procedures has been relatively fast and has contributed significantly to diagnosing and treating pulmonary diseases [1]. Chest X-ray (CXR) is still frequently used as a simple, inexpensive, and safe tool for diagnosing lung diseases, including pneumonia, tuberculosis, and COVID-19. [2] However, the identification and accurate interpretation of CXR findings still pose a significant problem because of lung disease's many and varied pathological patterns [3]. This challenge is magnified by the scarcity of well-annotated large medical image datasets for training deep-learning models [4]. Hence, the development of dependable and generalized models is a challenge.

Recently, deep learning, especially CNN, has proved to be a potential tool for automatically detecting and diagnosing medical images with high accuracy [5]. Nonetheless, CNNs have inherent drawbacks in expressing long-distance relations and global context in images, essential for detecting intricate and minor lung pathologies. [6]. To overcome these issues, transformer-based models have been introduced, which are very efficient in handling sequential data and capturing the global context [7]. Due to self-attention mechanisms, transformers can capture the interactions within an image and improve upon image classification tasks. Though CNNs and transformers have shown outstanding performance in medical imaging, their black-box nature is a significant issue for clinicians [8]. Explaining the predictions made about medical images is essential to prevent the usage of unreliable and untrustworthy models in clinical decision-making. Grad-CAM (Gradient-weighted Class Activation Mapping) is one of the most popular methods to explain the decisions made by deep learning models. It underscores the areas of an image that are more important in predicting a model

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and provides clinicians with more insights into the decision-making [9].

In this paper, we propose Trans-CAMNet, a new framework that integrates the benefits of transformer-based structures with Grad-CAM interpretability for more accurate and transparent lung disease categorization [10]. The proposed model uses CNN and transformers to improve feature extraction and context modeling; Grad-CAM enables the visualization of the model's decision-making process. The performance of Trans-CAMNet is assessed using the COVID-19 radiography dataset, and it is shown that Trans-CAMNet outperforms conventional CNN structures in terms of accuracy and explainability.

The objectives of this work are as follows:

- This study introduces Trans-CAMNet, a novel hybrid architecture that integrates transformer-based models and Grad-CAM for improved classification and interpretability in pulmonary disease diagnosis.
- This study compares the proposed architecture with state-of-the-art CNNs.

The following study sections are discussed: Section 2 describes the related studies. Section 3 discusses the materials and methods used in the study. Section 4 presents the results and discussion, and Section 5 concludes the study.

2. Related Work

Deep learning has advanced in recent years and enhanced the ability to analyze CXR images for diagnosing and comprehending thoracic diseases, including COVID-19 [11]. Recent work has explored strong and deep neural networks, ensemble models, and explainability methods like Grad-CAM, Grad-CAM++, and LRP to improve classification and explainability [12]. When used in different datasets, these approaches demonstrate the increasing role of AI-based instruments in enhancing diagnostic accuracy and aiding clinical management decisions. In this direction, Degerli et al. [13] used five deep neural networks (DNNs) to jointly localize the COVID-19-affected region and estimate the severity level of the infection based on CXR images. The approach used infection maps to explain the areas involved in the disease. QaTa-COV19 dataset was used in the study to offer annotated CXR images for COVID-19 diagnosis. By integrating multiple DNNs, the model performed reasonably well in detecting infected regions and severity levels, which is essential for clinical applications. Similarly, Mahmud et al. [14] used a convolutional neural network (CNN) for the multiclass classification of thoracic diseases, including COVID-19. For details, it could extract the hierarchical features with the help of depth-wise convolution, where the convolution layers were applied with different dilations. The model's performance was tested on three different data sets to demonstrate that it applies to different imaging sources. Chetoui et al. [15] used EfficientNet B7 as a CNN architecture to analyze CXR images from datasets such as BIMCV COVID-19+, RSNA, NIH, Montfort, and others. For explainability, Grad-CAM was used to explain the model's decision-making by visualizing regions of interest in the CXRs. The study also noted that the model could achieve high classification accuracy because of EfficientNet's specified network scaling method and feature extraction. Further proving its real-life capability, it could simultaneously operate on different datasets to increase efficiency.

Karim et al. [16] proposed a model comprising four CNN base learners and a Naïve Bayes as a meta-learner. In this work, four CNN architectures are used as base classifiers, where a Naïve Bayes meta-classifier is used to classify multiple classes of thoracic diseases, including COVID-19. The approach built upon integrating multiple CNNs took advantage of the synergistic learning capability and eliminated the overfitting problem. This model was applied to the Kaggle RSNA dataset to prove its ability to classify and interpret the CXR images accurately. In another study, Lee et al. [17]proposed and implemented an explanatory clustering framework called DeepSHA with a VGG-19-based model. DeepSHA offered explainable AI to cluster similar CXRs and then interpret the clustering to help diagnose. The framework was applied to public datasets, and its advantage was in providing interpretable clusters of similar cases, which would help study diseases and make clinical decisions. Altogether, these works highlight the possibility of using modern deep-learning methods with CXR images to diagnose COVID-19 and other thoracic pathology. Therefore, all the review articles show how deep learning techniques can help analyze CXR images to classify and diagnose thoracic

diseases, including COVID-19. The demonstrated high performance on various benchmarks also highlights the great promise of deep learning for transforming medical imaging into highly accurate, reliable, and explainable tools to enhance diagnostics and treatment of patients.

3. Methods Used

3.1 VGG-16

VGG-16 is a deep convolutional neural network structure on the Visual Geometry Group initiative of the University of Oxford [18]. This model attracted much attention due to its excellent performance and the simplicity of its model when it was crowned the winner of the ILSVRC. Its design principles have become a vital architectural concept in deep learning, even in the case of image classification [19]. VGG-16 consists of 16 weight layers: A model with 13 convolutional layers and three fully connected layers. The architecture is uniform, with 3 x 3 convolutional filters used throughout the system, with a filter stride of one [20]. These filters allow for preserving the input dimensions when extracting local spatial patterns in the convolutional layers. The network has twice as many filters at the deeper layers (for example, 64, 128, 256, 512) to learn features at successive levels [21]. Max pooling is done using a filter of size 2x2 and a stride of 2 after every few convolutional layers to decrease the spatial size and work at a more abstract level. The last part of the network consists of three fully connected layers, where the previous layer implements the SoftMax activation to output the class probability [22]. At its release, it offered one of the highest performances for large datasets like ImageNet. In addition, specific pre-trained versions of VGG-16 are being introduced in various transfer learning projects [23]. Researchers have used the learned features for other computer vision applications, such as object detection, medical imaging, and style transfer [24].

3.2 ResNet50

The ResNet-50 model is a well-known deep convolutional neural network devised by Microsoft researchers in their paper "Deep Residual Learning for Image Recognition," published in 2015. This model is from the ResNet family, which proposed residual learning to overcome the problem, including vanishing gradients and performance degradation, that might be encountered when training intense networks [25]. ResNet-50 is a full-residual 50-layer model and is one of the most frequently used networks because of its depth and computational complexity [26]. The main advancement of ResNet-50 is the use of residual blocks. A residual block is built from the shortcut connections through which the model can skip one or several layers during the forward and backpropagation computation [27]. These are often known as skip connections, which endow the network with an ability to learn residual mapping rather than direct mapping [28].

ResNet-50 architecture has 48 convolution layers, one max pooling layer, and only one fully connected layer. It uses bottleneck residual blocks, where each block has three convolutional layers: As for the convolutional layers, there's always one 1x1 layer for downsampling, one 3x3 layer for feature extracting, and the third 1x1 layer for upsampling [29]. This design helps reduce computational costs, although it results in high representational power. In addition, performing batch normalization after each convolutional layer helps stabilize the training process and accelerate the convergence speed. ResNet-50 has performed well on many benchmarks, including the ILSVRC [30]. The pre-trained ResNet-50 model is commonly used for transfer learning, and researchers can further modify it as per the application domain for analyzing X-ray images, detecting tumors, or classifying satellite images [31].

3.3 Inception-V3

Inception-V3 is a deep convolutional neural network, a third version of Inception architecture proposed by Google in 2015. This was pointed out in a paper by Christian Szegedy et al. titled 'Rethinking the Inception Architecture for Computer Vision.' Compared to the previous models, the model under consideration expands on the existing algorithms and brings new methods for increasing the speed and accuracy of computations [32]. Inception-V3 is one of the most used architectures in computer vision tasks, especially image classification. The structure of Inception-V3 architecture is such that it performs well on large-scale image classification problems. It uses inception modules to extract features at various scales due to parallel 1x1, 3x3, and 5x5 convolutions [33]. These outputs are concatenated to cover a variety of spatial features efficiently. To enhance computational efficiency, the model proposes factorized convolutions or using two consecutive and smaller kernels (e.g., 5x5)

instead of one large one (e.g., 3x3) with a predictable decrease in accuracy and size of the parameters. Furthermore, batch normalization is used heavily across the layers for training purposes and to prevent overfitting [34]. It is also important to note that the Inception-V3 network is computationally efficient yet has achieved high levels of accuracy. The model does this by including auxiliary classifiers as part of the training process to assist the training in case of vanishing gradients. In addition, label smoothing applied to the loss function enhances the generalization because the model stops making nearly specific predictions [35]. Together with the Inception modules developed with much care, these techniques make Inception-V3 work efficiently and accurately on benchmarks such as ImageNet and more efficiently than deeper networks [36]. Inception-V3 has shown great versatility in many applications, from image classification transfer learning to feature extraction [37]. It is typically used in object detection, diagnosing medical images or images in general, and even art-related tasks such as transferring style [38].

3.4 DenseNet169

DenseNet-169 is a type of deep convolutional neural network of the DenseNet family, which was presented by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger in their work "Densely Connected Convolutional Networks" in 2017. DenseNet architectures were created to overcome the shortcomings of traditional deep learning structures utilizing the dense connectivity method, which implies the direct connection of every layer of the neural network to any other layer in a feedforward manner [39]. This unique approach has distanced DenseNet as one of the most efficient architectures for recognition of images [40]. The DenseNet-169 model combined 169 layers, including the convolutional, pooling, and fully connected layers [41]. In DenseNet, the idea is to feed all the feature maps of a layer to the subsequent layers and take in all the previous layer's feature maps [42]. This is accomplished through dense blocks where feature maps are concatenated instead of summed, as in ResNet networks [43]. Transition layers are employed between these blocks of high density for feature maps down sampling and dimensionality reduction [44]. The growth rate, another hyperparameter in DenseNet, determines the number of new feature maps each layer in the network creates to balance the computational complexity and model capability [45].

Another favorable point that can be identified with DenseNet-169 is the utilization of parameters [46]. Compared to the conventional architectures in which many parameters are needed to pursue high accuracy, DenseNet adopts dense connectivity to keep feature reuse low [47]. This leads to better gradient flow during backpropagation and easier model training, even with fewer parameters. Compared to other architectures, such as ResNet and ResNeXt, DenseNet-169 is best suited for learning detailed features in datasets and is, therefore, well suited for image classification, segmentation, and other vision-based tasks [48].

3.5 Proposed Trans-CAMNet

In this research, we proposed a fine-tuned Vision Transformer (ViT) model to classify chest radiograph images from the COVID-19 Radiography Dataset. Vision Transformer architecture is appropriate for medical imaging tasks since it uses a self-attention mechanism to capture long-range dependencies and global contextual information [49]. In the proposed model, the deep neural network is trained on a large-scale dataset to obtain the general features and then trained on the COVID-19 Radiography Dataset for tailoring the CXR images. The Vision Transformer takes an input image and partitions the input image into fixed spatial regions such as 16×16. The patch is then flattened into a vector and mapped into the fixed-dimensional embedding space [50]. These are supplemented by a learnable class token and position-specific positional encodings to feed to the transformer encoder. The encoder, implemented as a stack of several instances of the multi-head self-attention mechanism and feedforward neural networks, can learn global relations between patches. This approach helps the model to determine regions in chest radiographs that are important to distinguish between COVID-19, lung opacity, pneumonia, and normal cases [51].

We use a transfer learning approach to implement the Vision Transformer for the COVID-19 Radiography Dataset. A labeled chest radiograph is used to fine-tune the pre-trained ViT, thereby enabling it to modify the learned features for the distribution of the dataset [52]. Fine-tuning is working on the model's weights, and this can be done using a supervised learning approach where the loss can be optimized to get better results with the classes. Also, data augmentation and regularization are used, with the data size relatively small in this project, to avoid overfitting. The fine-tuned Vision Transformer shows substantial performance enhancements in diagnosing chest radiographs, using its capability to model global dependency and recognize the subtle differences in the radiographic

features of COVID-19 [53]. Additionally, the attention maps of the model also make interpretation easier since they point out the areas that are most relevant to the prediction in the obtained CXR images. These attention-based visualizations are consistent with the radiological diagnosis, making the model accurate and clinically usable. The concept of the proposed fine-tuned Vision Transformer model indicates that transformer-based models can be used to solve issues in medical image analysis. By incorporating external knowledge and learning the characteristics of chest radiographs, the model provides high accuracy on the COVID-19 Radiography Dataset and advances the research of AI approaches to COVID-19 detection and diagnosis. Figure 1 describes the workflow used in the study.

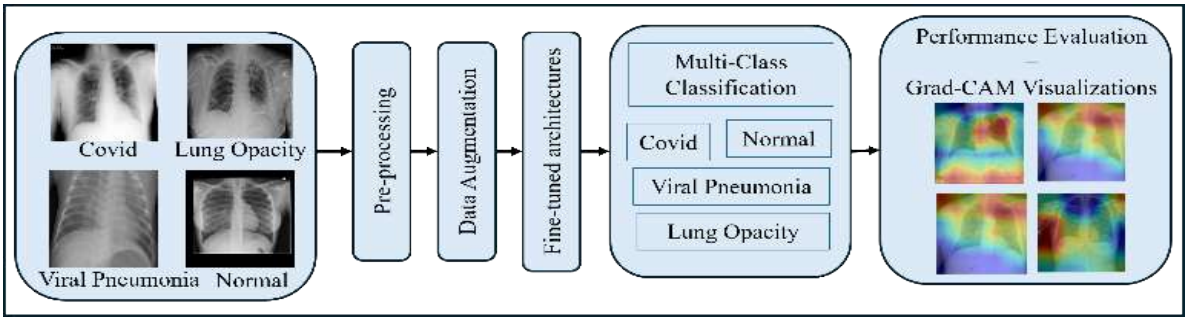


Figure 1: Workflow used in the study

4. Experiment

4.1 Dataset Used

The dataset used for the study consists of four disease categories: COVID-19, Normal, Viral Pneumonia, and Lung Opacity. The training and testing split is 70:30. The COVID-19 category consists of 3,616 images; from them, 2,531 images are utilized for training, and 1,085 images are used for testing. The most extensive files, containing 10,200 images in the Normal category, have been split between 7,140 images for training and 3,060 for testing. The Viral Pneumonia category contains 1345 images; of them, 941 are used for training, and 404 are used for testing. For the Lung Opacity, the category comprised 6,012 images, with 4,208 for training and 1,804 for testing. This means the model addresses various diseases and is trained and tested equally for all disease groups, making it reliable and accurate.

4.2 Evaluation Metrics

All standard measures were used to assess the outcome of the proposed models, such as Accuracy, Precision, Recall, and the F1-score. Accuracy calculates the ratio of the total number of instances correctly predicted to the total number of cases. Recall measures the model's capability of correctly identifying positive samples without counting false samples, and it is essential in reducing wrong classification. Recall measures how many positive actual cases the model identified. The F1-score, the measure of precision and recall in equal proportion, is helpful in the case of an unbalanced set of data. All these metrics, taken together, present a strong framework by which one can perform a comparative analysis of the strengths and weaknesses of each model to determine their ability to predict.

4.3 Results

The ability of the models to perform in terms of features such as the accuracy, precision, recall, and F1-score of the identified models, VGG-16, ResNet50, Inception-V3, DenseNet-169, and Trans-CAMNet is valuable information regarding each model's suitability. As each model corresponds to a different architectural complexity and ingenuity tier, the experiment (Table 1) shows how the performance differs on the given dataset. VGG-16, the oldest architecture among the architectures under comparison, has a test accuracy of 94.06%, precision of 84.62%, recall of 79.70%, and F1-measure of 82.09%. This can be attributed to its inability to perform residual or dense connections, preventing it from learning deeper hierarchical features excellently. The precision and recall are somewhat lower, implying that several images are misclassified, and VGG-16 is not suited for complex patterns of a given dataset. ResNet50 yields a much better result of 95.70 % accuracy, 93.61 % precision, 97.74 % recall, and a f1- score of 95.63%. The high recall suggests that ResNet50 has excellent actual

identification capacity. Its residual architecture helps reduce the vanishing gradient problem; thus, the model can train deeper networks. The high percentage of true positives and true negatives focuses on the stability of the measure between precision and recall. Similar performance is improved in Inception-V3 by attaining an accuracy of 97.13%, precision of 97.98%, recall of 91.79%, and F1-score of 94.79%. The inception modules mean multiple-scale filtering, allowing the model to get high-level features efficiently. This leads to better precision than ResNet50, meaning it has fewer false positives. DenseNet-169 achieved an accuracy of 97.96%, precision of 92.83%, recall of 95.48%, and F1-score of 94.13%. Due to its condensed network connections, this architecture entails reusing features and gradients, making learning extraordinary. Its high recall means it is good at identifying true positives.

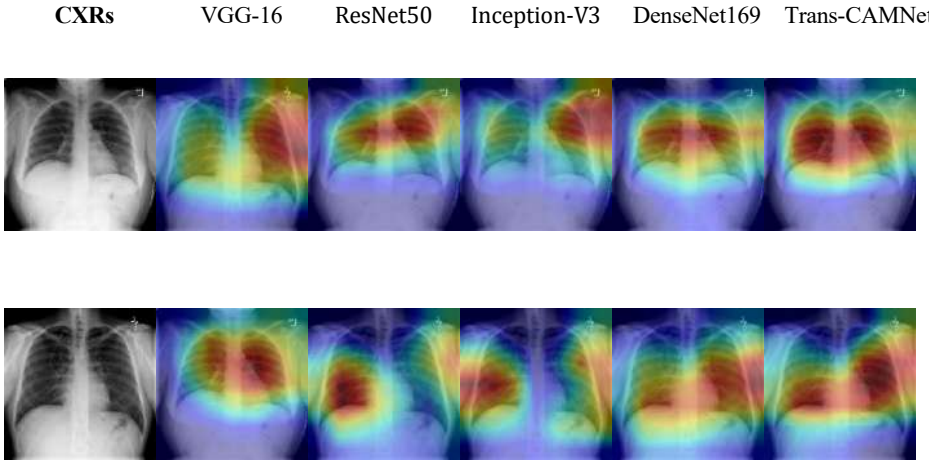
Table 1
Performance of different models.

Model	Accuracy	Precision	Recall	F1score
VGG-16	94.06	84.62	79.70	82.09
ResNet50	95.70	93.61	97.74	95.63
Inception-V3	97.13	97.98	91.79	94.79
DenseNet169	97.96	92.83	95.48	94.13
Trans-CAMNet	98.33	97.98	98.56	98.27

The proposed Trans-CAMNet has the highest overall accuracy of 98.33%, precision of 97.98%, recall of 98.56%, and F1 score of 98.27%. The nearly optimal values of precision and recall demonstrate excellent reliability, which is especially valuable for tasks where false positive and false negative results need to be avoided. The choice of model depends on the specific application requirements, as Trans- CAMNet is the best solution for critical cases with the highest level of needed accuracy and favoring balanced precision and recall values. This model may be improved by developing vision transformer architectures with attention to focus on the most essential objects while preserving overall context. Figure 2 depicts the Grad-CAM visualizations of different models.

5. Conclusion

This research shows that the proposed approach of fine-tuning the CNN- -transformer can effectively classify pulmonary diseases from CXR images. The Trans-CAMNet proposed in this study yields impressive results with an accuracy of 98.33%, thereby out-competing traditional CNN-based models. When used as an interpretability tool, Grad-CAM enlightens the model's decision-making process and increases its suitability for clinical use. These results highlight the opportunity to incorporate transformer-based medical imaging architectures that increase diagnostic performance and interpretability. The proposed approach can serve as a basis for future work combining deep learning models with interpretability methods and ensure more accurate and explainable machine learning-based diagnostics of pulmonary diseases.



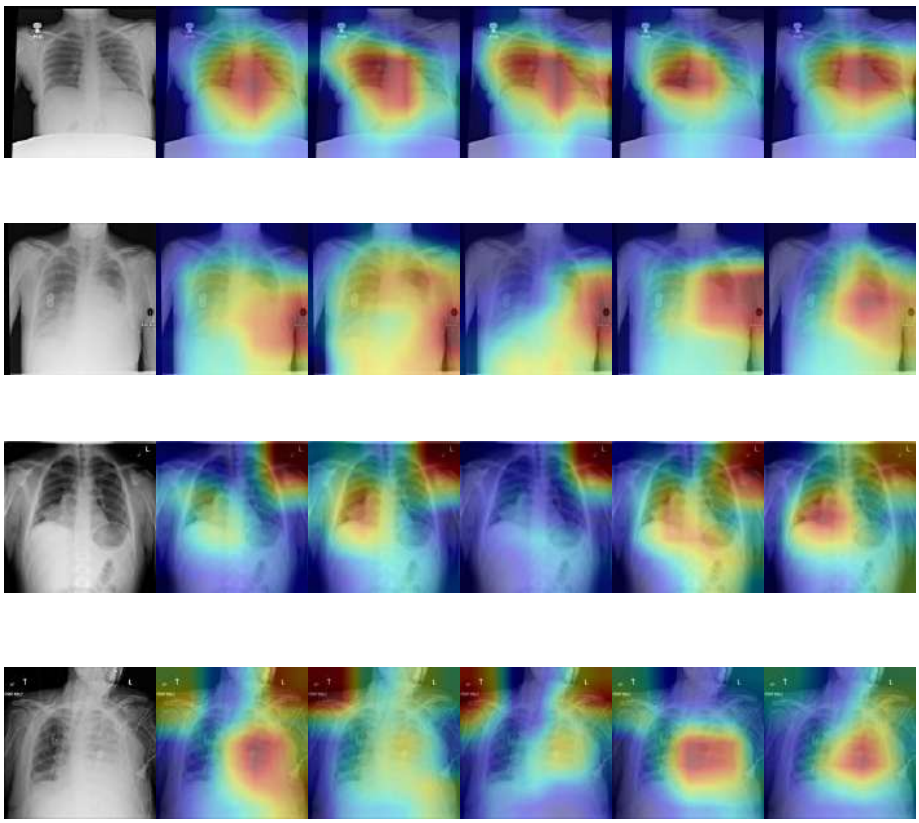


Figure 2: Grad-CAM visualizations of different models.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Using swarm algorithms to explore unknown areas in ROS2

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Abstract

This paper presents an investigation into using swarm algorithms to automate search, mapping, and localization tasks in multi-robot systems. The study focuses on developing effective coordination strategies for multiple robots operating within a shared network, aiming to explore unknown environments autonomously. The main objective of this research is to optimize route planning and minimize exploration time while enhancing system robustness through decentralized control and communication between agents. In addition, the work demonstrates the potential of swarm intelligence in improving the efficiency of collective decision-making processes. The proposed approach leverages the bee algorithm, a bio-inspired optimization method, to enable autonomous robots to explore, map, and localize within dynamic environments cooperatively. This study highlights the application of such systems in real-world scenarios, such as search and rescue missions, reconnaissance, and industrial automation, emphasizing their potential to address complex, large-scale tasks with improved scalability and adaptability.

Keywords

multi-agent bee algorithm, swarm intelligence, robot coordination, mapping, localization, decentralized control, autonomous exploration

1. Introduction

In today's world, robotics is one of the leading technological advancements, with robots increasingly being integrated into various aspects of everyday life, making the world more efficient and convenient. However, in most cases, robotic applications focus on individual units performing specific tasks, while the challenge of coordinating multiple robots as a unified system remains complex. When working with groups of autonomous agents, issues such as coordination, communication, and task distribution arise, requiring advanced strategies to ensure efficiency and effectiveness.

One promising approach to solving these challenges is swarm intelligence, a field inspired by the collective behavior of biological systems such as ants, bees, and flocks of birds. Swarm robotics leverages decentralized control, local interactions, and simple rules to enable multiple robots to work collaboratively, achieving tasks that would be difficult or impossible for a single unit. This methodology is beneficial for autonomous exploration, where a team of robots must navigate and map unknown terrain, find optimal routes, and adapt to dynamic environments.

This paper presents a system that utilizes swarm intelligence for autonomous exploration, localization, and mapping. The relevance of this research lies in optimizing robotic control strategies for drones and ground robots in unknown environments. Such a system could explore terrain efficiently and perform specialized search operations when equipped with cameras or sensors. A swarm of robots could be deployed for tasks such as locating missing persons, detecting gas leaks, or identifying hazardous substances, making them valuable in disaster response, environmental monitoring, and industrial applications. Moreover, advancements in artificial intelligence and edge computing have significantly enhanced the capabilities of swarm robotic systems, enabling real-time decision-making and adaptive behaviors in unpredictable environments. Swarm robotics is crucial in large-scale automation, from smart cities to space exploration.

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2. Related works

Swarm robots have some critical characteristics that differentiate them from other types of platforms, including but not limited to simplicity, size, scalability, cooperative ability, and communication capabilities [1]. In particular, two fundamental issues are their size and cost, as these aspects significantly affect the scalability of real swarm systems.

A solution has been proposed for operating a multi-robot system using a proprietary ROS-based architecture, demonstrating efficient real-time performance with multiple robots [2]. This solution relies on the first generation of ROS, which is now considered outdated due to the numerous enhancements introduced in ROS2. Modern ROS2-based systems offer improved facilities for distributed communication, real-time, and modularity, greatly enhancing the possibilities of building swarm systems [3].

More recently, there has been extensive research on the customization and deployment of the ROS navigation stack [4], which emphasizes the continued development of the ROS2 ecosystem and its applicability to autonomous mobile navigation tasks. However, such works mainly focus on single robots rather than their coordination within a swarm.

At the same time, there is a growing interest in applying swarm algorithms in mobile robotic systems, especially in robot-to-robot communication and decentralized control. Some developments, such as HeRo 2.0 [5] and HeRoSwarm [6], focus on building specialized hardware platforms for swarm systems. Despite interesting hardware solutions, these projects do not provide compatibility with ROS2, which limits their flexibility and repeatability of results in a scientific environment.

An alternative approach is offered by the ROS2swarm library [7], which is one of the first attempts to implement swarm behaviors in the ROS2 environment. It provides basic agent interaction patterns and simulation support but stays within a limited set of scenarios and does not fully evaluate the scalability or performance of the chosen algorithms.

The advantages of the proposed approach over existing solutions are a balanced ratio between low cost and performance, simplicity of the implemented swarm algorithm, and high efficiency of coverage of the studied territory. The developed system provides flexibility in setting parameters. It allows for a comprehensive analysis of the collective behavior of agents in various conditions - both in a homogeneous and a heterogeneous environment.

3. Methods and Materials

Robots and various approaches to territory exploration, including swarm algorithms, were used in the study. Simulation environments were employed to improve modeling and visualization accuracy, allowing for detailed analysis of robot behavior in virtual space. Additionally, tools facilitated navigation, mapping, and autonomous movement, enabling comprehensive testing and refinement of algorithms before real-world implementation.

The project used the following tools: RViz is a 3D robot visualization tool in ROS 2 that allows displaying sensor data, maps, robot trajectories, and other parameters in real-time. It supports extensions through plugins, and the librviz library allows embedding visualization capabilities into applications. Gazebo is a physical simulation environment designed to test robots in virtual conditions without the need for their actual operation. Nav2 is the ROS 2 navigation stack responsible for mapping, localization, route planning, and motion control in autonomous robotic applications. ROS 2 is a robot operating system that provides the necessary tools and libraries for developing, simulating, and controlling robots in various applications [8].

The robot was a four-wheeled structure with two axles connecting pairs of wheels. It was equipped with a sensor (LiDAR) to scan its surroundings, a camera for visual perception, and an odometry and mapping system for precise positioning and localization. Odometry was used to estimate the robot's movement, using sensors to measure the distance traveled and movement speed.

The SLAM (Simultaneous Localization and Mapping) algorithm allows robots to simultaneously build a map of the environment and determine their location without prior known information. The SLAM algorithm used odometry and scanner data for the project to locate and construct the map.

4. Swarm algorithms

The project is based on the use of swarm algorithms, and there are several conditions under which the best option was chosen:

- The algorithm should be oriented towards exploring the space, not just finding the optimal solution.
- Work in real-time, i.e., it should not require prior knowledge of the map.
- Distributes robots efficiently to avoid crowding them in one place.
- Takes into account obstacles and the changing environment.

The challenge may be how this map can then be merged, so a single starting area has been adopted for all robots, which will then explore the terrain from this point.

4.1. The particle swarm optimization algorithm

The particle swarm optimization (PSO) algorithm models the social-psychological behavior of a crowd. PSO is an optimization algorithm capable of solving nonlinear and multidimensional problems, typically achieving reasonable solutions quickly while requiring minimal parameterization.

The algorithm and its concept, Particle Swarm Optimization (PSO), were introduced by James Kennedy and Russell Eberhart in 1995 [9]. The central concept of the algorithm is the creation of a swarm of particles that move through their surrounding space (problem space) in search of their target or the location that best meets their needs, as defined by the fitness function [10]. In this algorithm, the swarm is fully connected; all particles exchange information, and each particle knows the best position ever visited in the swarm.

This approach focuses on presenting the best result for a particular robot and the swarm. Such an algorithm converges quickly to an optimal solution and works well if the goal is known. However, this approach is inefficient in a completely unknown environment, as there is no explicit 'best solution' for navigation. Robots may concentrate in one place instead of exploring uniformly. For these reasons, PSO is more suitable for optimization problems but is poorly suited for exploring new territory.

4.2. Ant algorithm

Ant Colony Optimization (ACO) is a widely recognized algorithm inspired by how ants forage for food and is frequently applied to tackle combinatorial optimization problems. Initially introduced by Dorigo, Maniezzo, and Colorni [11], this nature-inspired metaheuristic simulates the ability of ants to discover optimal paths between their nest and food sources, successfully addressing shortest-path problems without prior knowledge of the problem's structure [12]:

$$p_{i,j} = \frac{\left(\tau_{i,j}^{\alpha}\right)\left(\eta_{i,j}^{\beta}\right)}{\sum_{k \in N}\left(\tau_{i,k}^{\alpha}\right)\left(\eta_{i,k}^{\beta}\right)}, \quad (1)$$

where $\tau_{i,j}$ — the amount of pheromone on the edge (i, j); α — a parameter controlling the influence of the pheromone; $\eta_{i,j}$ — the attractiveness of the edge (i, j), usually equal to $\frac{1}{d_{i,j}}$, where $d_{i,j}$ is the distance between nodes; β — a parameter controlling the influence of attractiveness.

Continuous Ant Colony Optimization (CACO) is an improved version of classical ACO adapted for problems in continuous space rather than discrete graphs [13]. Unlike ACO, where ants move between predefined nodes, in CACO, the robots move freely along coordinates and update a 'virtual pheromone' in a region of space [14]. This algorithm allows more efficient exploration of unknown terrain, primarily when the map structure is unknown in advance. This makes CACO suitable for the task of collective map construction by robots: it provides flexibility of movement, allows dynamic adaptation to changing environments, and does not require a predefined grid of routes.

4.3. Bee algorithm

The Bee Algorithm is a metaheuristic optimization algorithm inspired by the foraging behavior of real bees. It simulates the work of scouts searching for new sources of nectar and worker bees intensifying their search in the most promising areas.

In the bee algorithm, agents (bees) must find optimal solutions, similar to how honeybees find food sources. Bees share information about the location of food sources with other colony members using a waggle dance. This dance, which consists of alternating turns and waggles of the abdomen, conveys two important parameters: the distance to the food source and its direction [15].

The duration of the waggle indicates the distance, and the angle between the sun and the movement of the abdomen on the comb indicates the direction. In the algorithm, other agents can apply these instructions and follow the best solution, similar to how bees navigate to the best food sources. The decision-making mechanism depends on the quality of the solution, which allows agents to choose more promising options.

The algorithm uses Path Integration (PI), a method in which each agent updates its position, considering all the distances traveled and changes in direction. This allows agents to efficiently explore the space and find optimal solutions, similar to the behavior of insects using this navigation method.

Multi-agent systems inspired by bee behavior uniquely adapt to environmental changes and efficiently solve resource allocation problems. Such systems are based on the principles of self-regulation, where each agent acts based on local information and interacts with other agents to achieve a common goal. Importantly, these systems can be used to develop efficient algorithms and better understand the mechanisms of collective decision-making in nature [16].

However, this approach may have some drawbacks, such as a tendency to get stuck in local minima, which may make it difficult to effectively explore large or complex areas, as robots may be limited to exploring only nearby areas rather than covering all possible areas. Another obstacle is the need for multiple robots to provide sufficient coverage, which may increase computational costs, especially if the number of swarm members or the size of the area to be explored is large. In addition, the bee algorithm may be sensitive to the initial placement of agents, which may lead to uneven coverage or insufficient exploration of the area in the context of dynamic search.

To address the challenges of local exploration and resource allocation, we utilize the multi-agent bee algorithm, a probabilistic approach to determine which areas should be prioritized by the agents. This is achieved by calculating the probability \(P(x) \) of selecting a specific point \(x \) based on its attractiveness, which is defined by the following formula:

$$P(x)=\frac{f(x)}{\sum_{y \in R} f(y)}, \tag{2}$$

where x — is a potential research point; R — is the set of all possible research points; $f(x)$ — is the attractiveness function of the point x, which can be defined as:

$$f(x)=\alpha \cdot d(x,B)+\beta \cdot g(x)+\gamma \cdot h(x), \tag{3}$$

where $d(x, B)$ — distance from point x to the nearest known boundary point; $g(x)$ — function estimating the potential of point x to become a boundary point; $h(x)$ — function taking into account the history of the study of point x; α, β, γ — weighting coefficients.

The following formula describes how a robot explores a point based on several factors:

$$t_i(t)=argma\, x_{x \in R¿(t)}\left[\omega^1 \cdot d(x,B)-\omega^2 \cdot d(x,s_i)+\omega^3 \cdot q(x)\right], \tag{4}$$

where $E(t)$ — set of points explored by other robots at time t; $d(x, B)$ — distance to the nearest known boundary; $d(x, s_i)$ — distance from the robot to the point; $q(x)$ — quality function of the point (potential to be a boundary); $\omega_1, \omega_2, \omega_3$ —weight coefficients.

At time t, each robot must choose a point $t_i(t)$ from the set of possible points R, excluding those already explored points represented by $E(t)$. The robot's decision is based on a weighted combination

of factors, allowing it to select points that offer the best coverage of the area, given the current conditions and constraints.

Finally, let *I(t)* represent the global information about the boundary points at time *t*. Each robot n_i updates its local information $I_i(t)$ as follows:

$$I_i(t+1) = I_i(t) \cup_j I(t) \vee_j n \in C(n_i, r), \quad (5)$$

where $C(n_i, r)$ is the set of robots within communication radius r from robot n_i.

The chosen approach reflects the core decision-making process of the bee algorithm, prioritizing exploration based on a combination of multiple factors. Robots can effectively balance between exploring new areas and reinforcing previously identified boundaries by utilizing a probabilistic approach to select points based on their attractiveness. The weighting coefficients in the formula allow for flexibility in adjusting the impact of different factors, such as the proximity to known boundaries, the distance from the robot, and the potential of a point to become a boundary. This adaptability makes the bee algorithm particularly effective for dynamic environments where exploration and resource allocation must be adjusted in real-time. Furthermore, the formula accounts for the collaborative nature of the swarm, where each robot's local information is updated through communication with nearby agents, ensuring that the exploration process remains efficient and comprehensive. By selecting the most promising points based on these criteria, the algorithm maximizes the overall coverage and effectiveness of the swarm, ensuring a balance between local and global exploration objectives.

5. Robot architecture

5.1. The base structure of the robot

Below is a structure that shows how the different parts of the robot (sensors, steering mechanisms, wheels) are linked through the transformation system in ROS 2. The presence of global (map, odom) and local (base_link, wheel_link) frames allows the robot to determine its position in space and control movement correctly.

In ROS 2, nodes are the fundamental building blocks of the system. A node is an executable that performs a specific task, such as reading sensor data, processing that data, or controlling the robot's motors. Nodes communicate with each other using topics, services, and actions. They can be run on the same machine or distributed across multiple machines in a network. The flexibility of ROS 2 nodes allows for modular design and efficient control of robot systems [17].

Each robot in the system operates within its namespace, ensuring that multiple robots can function simultaneously without interference. This structure is crucial in swarm robotics, where each unit must manage its own transformations while also exchanging information with others.

Additionally, ROS 2 supports real-time processing, enhancing robotic operations' accuracy and responsiveness. By leveraging the ROS 2 middleware, robots can efficiently synchronize sensor data, execute navigation commands, and dynamically update their internal state based on environmental changes. This approach improves the scalability and robustness of autonomous robotic systems, making them suitable for large-scale deployments in real-world applications.

Figure 1 shows a graphical visualization of the ROS 2 frame tree (TF) created with tf2 and the "view_frames" tool and converted into a block diagram. This diagram shows the hierarchy and relationships between the robot's different coordinate systems (frames) in the simulation. Two conventional groups, "sensors_group" and "steering_group", are responsible for the operation and stability of the sensors and allow the distribution of responsibilities between components.

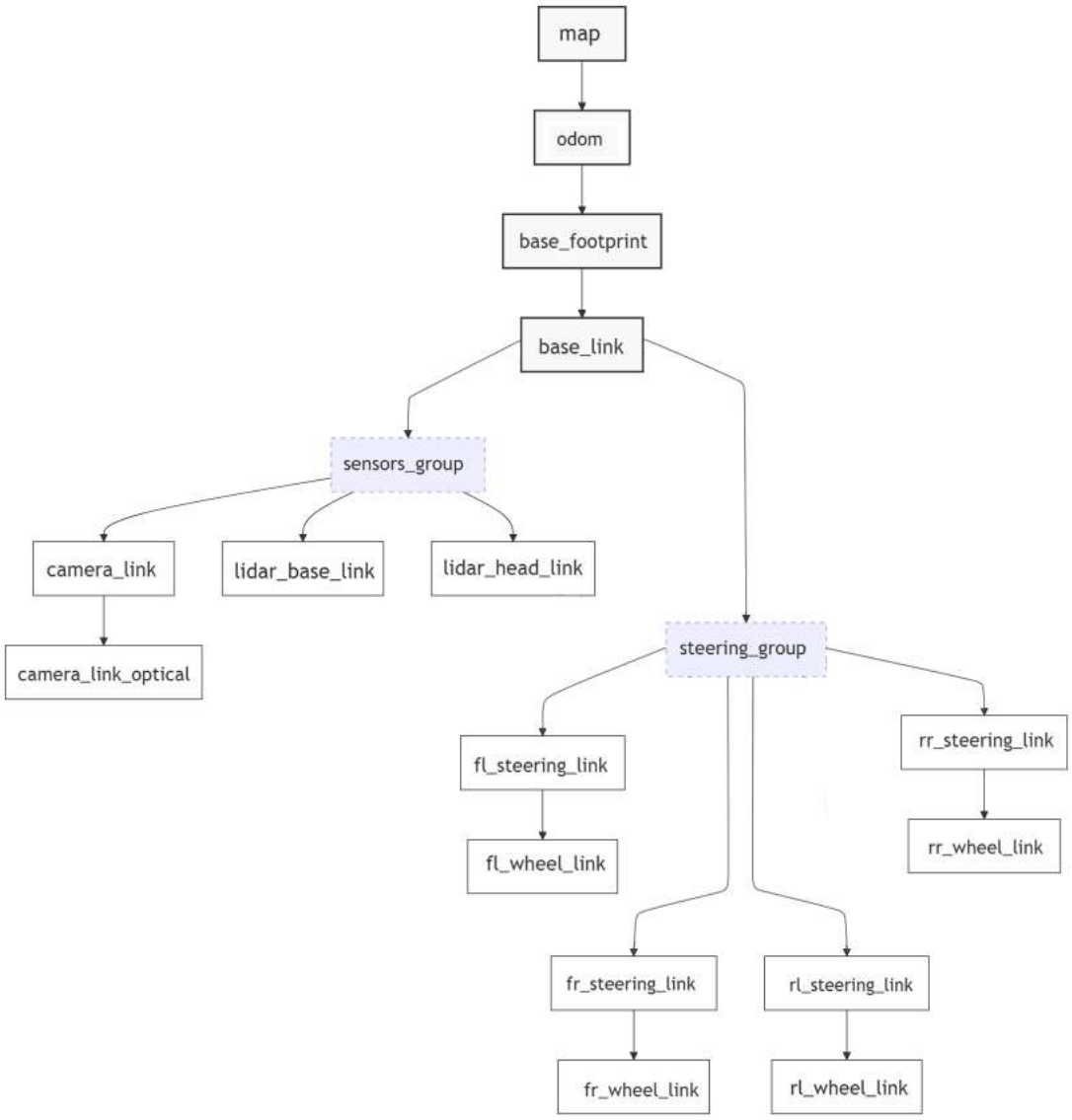

Figure 1: Visualization of robot architecture

The top node of the tree is “map”, the global coordinate system. From it there is a link to “odom” (the odometric system), which is updated over time and contains information about the robot's position relative to the starting point. The structure is then connected to “base_footprint”, the robot's base point representing its position on the surface.

From “base_footprint” follows a connection to “base_link”, which is the robot's main frame to which all other components are linked.

Figure 2 represents the robot that corresponds to the graph above. This image was taken in a gazebo simulation and shows the visual characteristics.

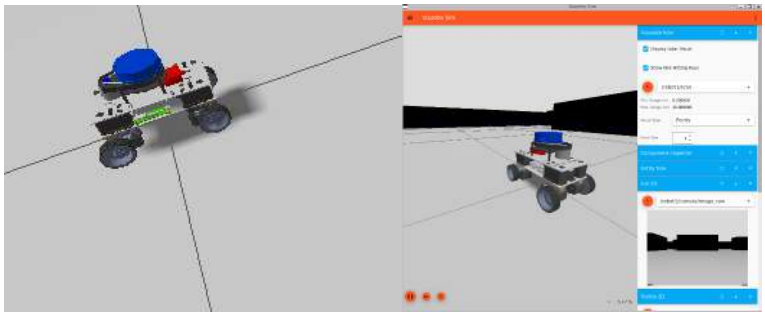

Figure 2: Visualization of robot in Gazebo sim

5.2. Using SLAM in robot architecture

5.2.1. SLAM

The robot building process also considers the future use and availability of the model and system for mapping and localization in a dynamically changing environment. The robot-building process also considers the future use and availability of the model and system for mapping and localization in a dynamically changing environment. With such input parameters, ensuring that these systems are available for scaling and integration into different scenarios is very important. For example, in an urban or manufacturing environment, a robot faces moving objects, changing infrastructure, or unpredictable disturbances. To function in such environments, the system must quickly process data from sensors (lidars, cameras, gyroscopes) and instantly adjust its route, avoiding collisions and minimizing delays. This is especially critical in systems with swarm intelligence, where many robots interact to fulfill a common task – for example, when searching for survivors in an emergency zone or synchronized delivery of goods to a warehouse.

This is where SLAM (Simultaneous Localization and Mapping) comes to the fore. This technology allows each robot to simultaneously build a map of an unknown environment and determine its position in it. Recently, the demand for intelligent robotics has increased, and there are more advanced approaches to detecting the environment for robots [18]. The object can be a domestic robot, autonomous vehicle, planet rover[19], uncrewed aerial vehicle (UAV) [20] [21] or other automated systems. SLAM becomes indispensable in environments with no pre-prepared terrain map or the device's position is unknown, making it a versatile tool for various tasks. Due to the rapid development of robotics, SLAM is attracting increased interest from academia and industrial developers.

SLAM systems can collect environmental data from different types of sensors: laser, acoustic, or visual. For example, robots with cameras analyze images to determine their position and orientation in space. This approach, known as VSLAM (Visual SLAM) [22], has several advantages: reduced hardware costs, simplified object recognition and tracking, and access to detailed visual and semantic data. The resulting images are used for navigation and computer vision tasks such as semantic segmentation or object detection due to the large amount of information they contain.

In the SLAM problem, filters continuously refine estimates of an object's position and velocity using imprecise location measurements. They also improve the accuracy of spatial landmark positions.

The Kalman Filter is an algorithm used to estimate the state of a system under uncertainty [23][24]. It is applied in SLAM, navigation, signal processing, and other fields where state estimation based on noisy measurements is required. In the original implementation of the SLAM algorithm, the primary source of information about the robot's movement was odometry obtained from wheel rotation. Despite its simplicity and widespread use, this method has several significant limitations. Odometry errors accumulate over time due to wheel slippage, interaction with uneven or slippery surfaces, as well as during sudden braking or collisions with obstacles. In addition, wheel odometry does not provide absolute measurements of position and orientation in space, which is especially critical during long-term autonomous operation. In the absence of external correction, for example, due to visual or lidar sensors, the system is prone to drift. For this reason, modern SLAM systems implement a multimodal approach to state assessment, combining odometry data with information from LiDAR, cameras, or inertial measurement units (IMUs). Such sensor integration can significantly improve localization accuracy and the algorithm's resistance to various types of noise and external influences. This study uses a camera and LiDAR as the primary data sources, eliminating the reliance on odometry while improving the system's robustness in simulated conditions.

The RF2O (Range Flow 2D Odometry) method estimates robot odometry by comparing successive laser scans. The basic idea is to find the optimal transformation between two scans that minimizes the point-matching error:

$$\left(R^{¿}, t^{¿}\right) = arg\min_{R,t} \sum_{i=1}^{N} |R \cdot p_i + t - q_i|^2, \tag{6}$$

where p_i — is the point from the previous lidar scan, q_i — is the corresponding point from the current scan, R — is the rotation matrix, t — is the translation vector, N — is the number of matched points.

This approach (6) helps to improve the accuracy and stability of odometry estimation, especially in dynamic and complex environments where traditional methods may have limitations.

5.2.2. Merge maps

In an environment with many robots, the system handles each robot's output separately from the others using the delegation method through namespaces. When each robot publishes a separate map to a separate topic in a namespace, it becomes necessary to merge these maps together. To merge the maps effectively, it is crucial to consider the raw data from each robot and factors like sensor noise, alignment errors, and differences in the local coordinate frames.

One common challenge is the misalignment of the maps, which can occur when the robots use different frames of reference or have slightly different odometry information. Several approaches can address this, including using Iterative Closest Point (ICP) algorithms and techniques like graph-based optimization. Additionally, careful handling of the transform (tf) between robots is required to ensure accurate map alignment. Even with these techniques, some artifacts may persist, particularly in areas where the robots' sensors had conflicting readings. These issues can be minimized by fine-tuning the merging process and employing robust alignment methods, leading to a more accurate global map. In Figure 3, pictures (a) and (b) show the local maps of two separate robots operating in different namespaces, where each robot builds its version of the environment. Figure (c) is a merged map, the result of merging data from both robots, where it can be seen that the map boundaries are aligned. However, there are artifacts and distortions, probably due to errors in coordinate alignment or tf-frames.

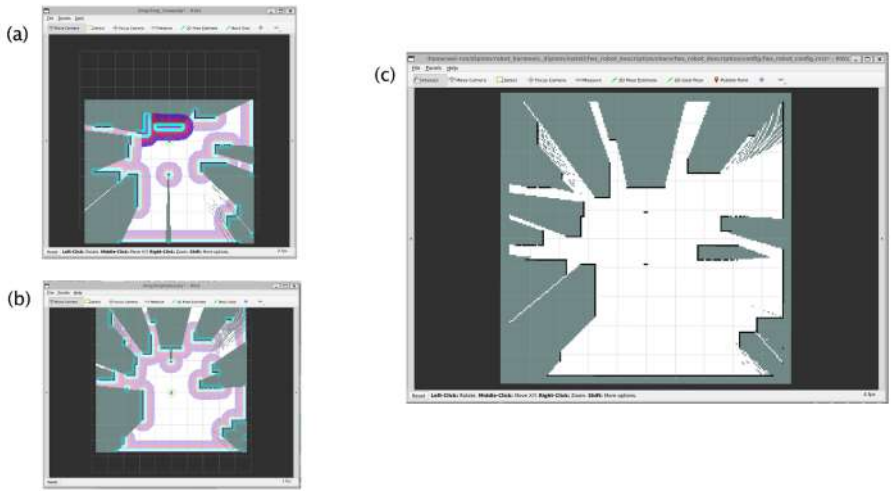

Figure 3: Visualization of merging maps from different robots

5.3. Using Navigation2 for path planning and obstacle avoidance

Navigation2 (Nav2) is a powerful navigation stack for ROS 2, designed for the autonomous movement of mobile robots. It is the successor to the classic ROS Navigation Stack from ROS 1, but offers an improved architecture, advanced customization options, and support for modern navigation algorithms. Nav2 is used for motion planning, path control, obstacle avoidance, and real-time map updates, making it an important tool in robotics for delivery services, autonomous warehouses, and service robots.

Nav2 follows a modular design, each component handling a specific part of the navigation process. Key components include the Planner Server, which builds a global route; the Controller Server for local movement control; the Behavior Tree Engine, which organizes navigation processes; and Costmap 2D, responsible for creating walkability maps. Due to the architecture's flexibility, Nav2 allows easy customization of the planning and traffic control algorithms for specific tasks.

Navigation2 supports integration with various sensors, including lidars, cameras, and IMUs, and works both in simulation (Gazebo, Isaac Sim) and on real robots. The ROS community actively develops the system, and researchers and companies use it in various projects. Support for hybrid AI algorithms, reinforcement learning (RL), and SLAM makes Nav2 a promising solution for dynamic environments.

ROS2 and Navigation2 include the SLAM Toolbox [25] as the core package for SLAM solutions. It provides real-time mapping capabilities for large areas through advanced graph implementations, making it well-suited for dynamic environments. With a focus on customizability, it also offers a variety of options to meet the specific requirements of specific use cases. At the same time, Navigation2 developers have shown great interest in supporting emerging Visual SLAM (VSLAM) approaches that can replace traditional methods that require expensive lidar sensors [26].

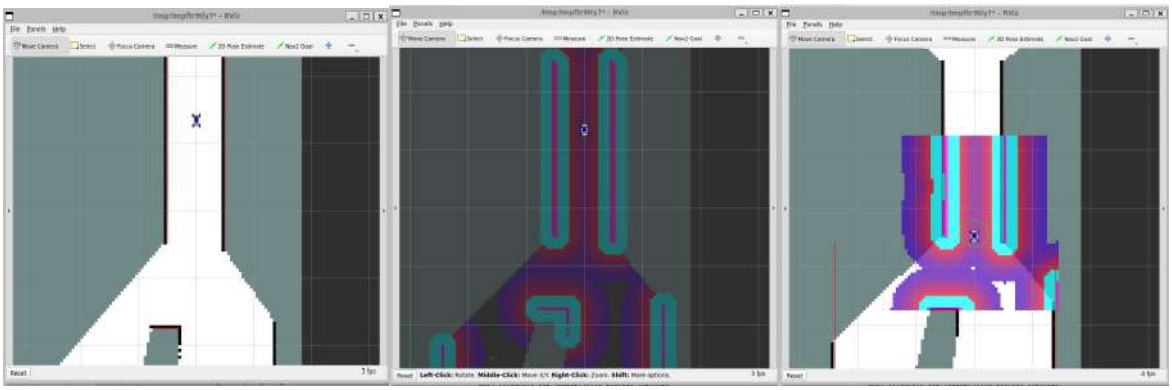

Figure 4: Visualized differences between SLAM map, global costmap and local costmap

6. Experiments

Several experiments were conducted with the robot system on different maps, scaling the number of robots used to build a map of an unknown area. In Experiment 1, a basic pattern was run where a swarm of robots searched for optimal routes to unknown areas using a static environment and tracking other robots with a sensor. In Experiment 2, a combined basic pattern was run and additional sensors and cameras were used to detect other robots in the swarm in a dynamic environment. These two experiments should help us analyze the difference in swarm behavior in static and dynamic environments, and their necessity and difficulty in scaling the swarm.

Three types of maps were used for Experiments 1 and 2: a rectangular box with obstacles inside, a corridor-type area, and an area around a large object. In all three types of maps, the robots had the same amount of time to cover as much territory as possible and return to the starting point.

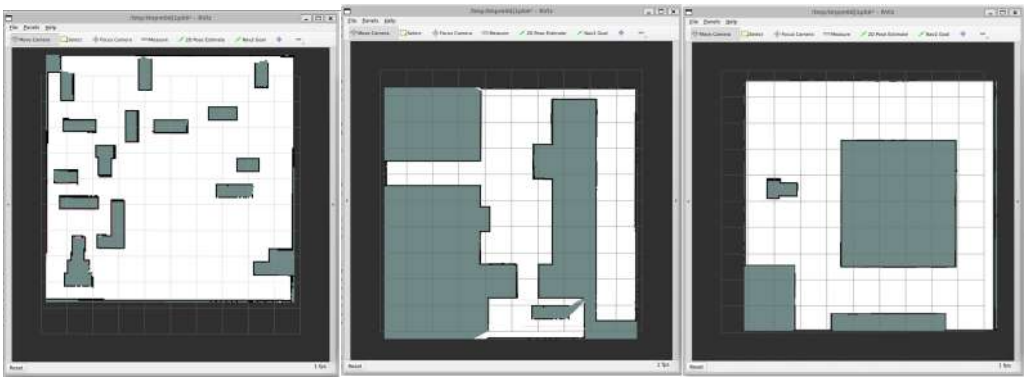

Figure 5: Available maps: a rectangular box with obstacles inside, a corridor-type area, an outer zone

Experiment 1 involves the use of the Multi-Agent Bee Algorithm, which allows scout robots to be used to cover a larger area for exploration.

Since LiDAR does not distinguish between robots and obstacles, robots may mistakenly see walls or other objects as other members of the swarm, which can sometimes alter their assessment of the area and cause one robot that has separated from the group to be unable to return to the swarm without outside intervention.

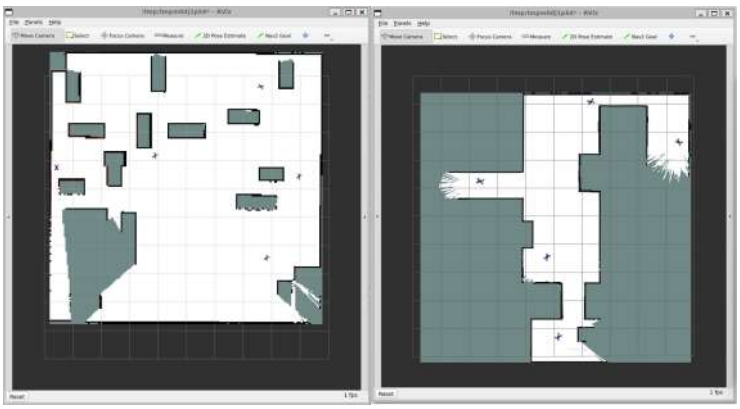

Figure 6: Example of system start-up

Experiment 2 used an algorithm similar to the first experiment but also created a dynamic environment in which the robots had to cover the territory, taking into account the possible emergence of new obstacles. Also, in a dynamic environment, a different number of robots in a swarm was tested, for a clear example of the scalability of the system. This simulation used the same types of maps as the previous experiment. The current setup of the robots differed from the previous one in that new sensors and cameras were used, which allowed them to accurately determine the positions of swarm members in a dynamically changing environment and avoid already marked and explored territories.

Table 1
Experiment results

Experiment	Number of robots	Coverage area, %	Type of map	Average Speed	Robots back in position
1	5	89	rectangular box area	43	5
1	5	72	a corridor-type area	37	4
1	5	85	outer zone	60	5
2	5	91	rectangular box area	46	4
2	5	83	a corridor-type area	36	3
2	5	85	outer zone	59	5
2	10	97	rectangular box area	40	10
2	10	89	a corridor-type area	44	9
2	10	92	outer zone	53	10

The essence of the experiment was that, despite new obstacles, the robots could correctly mark the map and find their way back to the starting position. The difficulty of this method was that the robots require a more complex setup and support, leading to an increase in the complexity and cost of such a swarm. Table 1 shows the results of two experiments, allowing us to analyze the system's stability in different situations and their advantages and disadvantages when scaling in a dynamically changing environment.

Future work will focus on improving the synchronization of robot movements, enhancing sensor fusion techniques, and optimizing the algorithms to handle increasingly dynamic environments with minimal human intervention.

7. Conclusion

The experiments demonstrated that the swarm robot system with basic and combined patterns can effectively explore unknown terrain in both static and dynamic environments. The first experiment showed that using the Multi-Agent Bee Algorithm allows scout robots to expand the exploration area quickly. However, LiDAR sensors' limitations sometimes lead to obstacle recognition errors. This can cause issues with individual robots returning to the formation, especially if they separate from the group and mistake walls for other swarm members.

The second experiment confirmed that adding new sensors and cameras improves the accuracy of robot and obstacle detection in a dynamic environment, which is crucial when the environment changes and new obstacles appear. Despite the increased setup complexity and higher system costs, these improvements enhance the swarm's stability and efficiency, which was clearly demonstrated across three different types of maps.

Comparing the results of the two experiments showed that the dynamic environment reduces the number of robots successfully returning to their starting position, particularly when the swarm size is small. However, increasing the number of robots to ten made the system more resilient, as confirmed by high coverage rates and a greater number of robots returning to the base. This demonstrates the swarm's scalability potential, especially when enhanced sensors and cameras are used.

The experiments confirmed that the swarm system can adapt to various terrains and conditions. The combination of basic and complex patterns, supported by additional sensors, proved effective when scaling the swarm. Nevertheless, the identified LiDAR limitations and the complexity of setting up dynamic systems require further improvements to enhance the swarm's autonomy and resilience in unpredictable environments.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Detecting Wildfire-Damaged Areas From Satellite Images Using Deep Learning

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Abstract

Rapid detection of forest fires is crucial to reduce their devastating impact on ecosystems and human lives. In this paper, we present an AI-based solution for forest fire detection using deep learning from satellite imagery using the ResNet50V2 convolutional neural network (CNN). The dataset used to train the model consists of 1,900 images (950 per class), carefully curated to reflect real-world scenarios of both active forest fires and undisturbed forests. Data preprocessing included image augmentation to reduce overfitting and enhance model performance. Transfer learning, model regularization, and reconstructed pooling layers were applied during training on this dataset, which was augmented with techniques such as random horizontal rotations, zooming, and cropping to improve model generalization. The model achieved 97.63% accuracy and 98.40% precision in detection. Forest fire detection using satellite images is very useful because CNN methods can detect and locate active fires more than once per hour. It is well known that the earlier a forest fire is detected, the more effective it is for people and the environment. This method can help to develop of new strategies for real-time fire monitoring systems, in addition to greatly enhancing wildfire management and prevention efforts. This study focuses not on early fire detection, but on identifying post-wildfire damage using deep learning techniques applied to satellite imagery.

Keywords
Forest; Forest fire; Detection; Deep Learning; ResNet50V2

1. Introduction

A forest is a closed area of trees, other plant species and animals at a certain level of closure, together with the invisible is defined as a living system and community in which organisms interact [1]. The world's forests cover a total cumulative area of a staggering 4.06 billion hectares, covering about 31% of the planet's land area [2]. Climate change is expected to have a particularly significant impact on boreal forests due to rapid and significant temperature increases in this region [3], as each additional degree of warming could result in a tripling of the area burned [4]. Therefore, the aim of this study is to determine how much land is destroyed after the fires are extinguished by using artificial intelligence (AI) integrated systems. By identifying affected regions after fire events, the proposed model can support post-disaster assessment and resource planning.

Deep learning, as a subset of AI, has the ability to enhance the detection rate of fires and other natural disasters using large datasets [5]. More specifically, image processing techniques have also been proposed that would benefit the response time by improving the ability to spot a forest wildfire in its early stages [6]. It is also noted that deep learning (DL) image classification models are able to successfully analyze visualization artifacts such as smoke and flames in order to determine the presence of fire [7]. DL models such as ResNet50v2 have recently achieved high accuracy rates in forest fire detection in remote sensing application systems.

ResNet50v2[8], a convolutional neural network model, effectively recognizes key details underlying images from image-trained data due to its layered structure. This model is particularly useful in building a forest fire detection system because it maintains its efficiency even with very large datasets [9]. The content of the image passes through the network with less distortion and easily through the use of "residual" connections, which enables ResNet50v2 to speed up the learning process, thus improving the

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overall accuracy [10]. This characteristic feature combined with the strength of the neuron structure, allows ResNet50v2 to be useful in practical problems requiring high accuracy, such as fire detection.

Wildfires can have a devastating effect on ecosystems, people, and economies especially in areas vulnerable to wildfires. Current methods of fire remote sensing via satellite still struggle with offering timeliness, precision, or flexibility. Most of the traditional approaches depend on systematic monitoring (by humans) or use local sensor networks. This aids in scaling detection but isn't helpful in real-time detection over extensive areas. An AI-based method that utilizes satellite images to quickly pinpoint the exact location of the wildfires and assist with rapid aid is highly essential.

For this study, we used the Forest Fire Detection Dataset presented by Khan and Hassan[11] and available from Mendeley Data. This dataset contains a large number of images specifically selected for the purpose of forest fire detection. It is a balanced dataset consisting of 1900 images in total, with 950 images belonging to each class. The comprehensive size of such a dataset also makes it suitable for the effective development of a DL model that can positively contribute to the early detection and monitoring of forest fires.

The purpose of this paper is to recommend an AI-based approach for fast and effective detection of forest fires. In this regard, the authors trained the ResNet50v2 model which was prepared on a large dataset for forest fire detection and evaluated the model's performance. The focus of this research is to find possible extensions to current fire detection systems and to emphasize the use of AI in the management of environmental threats.

2. Related Works

Over the past few years, there has been significant attention towards the applications of AI and DL on detecting forest fires [12]. Attempts have been made on the researches front to build models that help in detection of wild fires in real time, through the usage of computer vision as well as machine learning. Several satellite imaging as well as ground sensors, and unmanned aerial vehicles have been integrated into the wildfire monitoring systems that help in detecting, analyzing, and responding to these events in real time [13]. The detection of wildfires has also been effectively done through various DL structures.

Harkat et al. and Yang et al. [14,15] have shown that DL does not perform adequately due to limited data, generalization, interpretability, and missing features, but integration of DL with other methods can improve efficiency. Sathishkumar et al. [16] used DL based forgetting learning technique for forest fire and smoke detection. VGG16, InceptionV3 and Xception models were trained with fine tuning and their performances were compared. They utilized deep learning-based learning for fire and smoke detection, highlighting the potential of AI in early fire detection systems. In another study, Best, et al. [17] compared frozen VGG, 4-layer CNN, and fully trainable VGG for UML diagram classification and showed that the frozen VGG achieved higher accuracy with reduced sample size and required less computation time compared to the fully trainable VGG.

Achieving efficient and fast operation of endpoint devices is one of the achievements of Peng et al. [18] with their proposed fire detection algorithm. An effective balance between accuracy and speed is achieved by using quantization-compatible activation functions, a QARep component, and image size optimization using a YOLOv8 algorithm. While image transfer has a positive impact on accuracy, there is an impact on accuracy with respect to INT8 quantization, resulting in some loss of accuracy. The study by Ginkal et al. [19] explores the use of AI methods for forest fire detection. The study provides an AI-based framework for early detection of forest fires. The framework uses machine learning techniques to perform fire detection by combining color, motion and shape features. Features such as color probabilities, color histograms and image moments are used for fire region segmentation, classification, and verification. Experiments show that the proposed framework works with high accuracy and provides real-time processing time.

Another research article by Titu et al. [20] explores the integration of lightweight DL models for real-time fire detection using drones and edge computing. Using knowledge distillation techniques, the study develops DL models such as Detection Transformer (DETR), Detectron2, and YOLOv8. Using this approach, the YOLOv8n model achieved the highest accuracy (95.21%). In another study in a similar area, Anh et al. [21] offer a different approach to detecting forest fires with UAVs, using different color spaces in combination with correlation coefficients to determine the actual fire area.

Liu et al. [22] propose two AI agents armed with large digital databases that autonomously control fiber optic temperature monitoring systems and DL algorithms to detect fires in large commercial

spaces. The research examines the effectiveness and reliability of this combined approach and expresses how it can revolutionize fire safety measures when applied to large commercial spaces. In their work, Dampage et al. [23] propose the use of wireless sensor networks in conjunction with machine learning to detect wildfires at very non-extensive stages. Machine learning models are used to evaluate data gathered by sensor networks, so as to estimate the likelihood of a wildfire. In a second part, rechargeable batteries and a solar-powered power supply are used to ensure that the system remains energy efficient.

To summarize, previous research has shown that image-based wildfire detection can be performed with deep learning models VGG, Inception, and variants of YOLO. However, most of these works emphasize detection and monitoring using UAVs or ground sensors. Relatively few have attempted the post-wildfire damage identification using satellite images with high accuracy CNN architectures like ResNet50V2. Our study seeks to fill this gap by utilizing a powerful transfer learning technique for detecting wildfire damage using satellite imagery, providing a valuable resource for post-disaster evaluation and recovery design.

3. Methods

3.1. Data Collection and Data Pre-Processing

The dataset for forest fire detection is a comprehensive and carefully selected resource specifically designed to assist the development of algorithms for tasks such as forest fire detection and object detection. The images are the result of a search for different keywords in different search engines. As depicted in Fig. 1, designed for the binary problem, the dataset of 1,900 images (950 images per class) is divided into two main categories: The first category contains images documenting active forest fires, while the second category contains images of undisturbed, fire-free forest areas.

Figure 1: Dataset content examples [11].

To improve the performance of machine learning and DL models, all images in the dataset are three-channel with a spatial resolution of 250 × 250 and consistent formatting. Each image in the dataset is carefully reviewed and pre-processed to remove irrelevant elements, such as human activity or firefighting equipment, to focus only on fire and non-fire regions. This is important for the model that will be used for training, as it eliminates false positives when the model is asked to identify areas of the forest that have burned and those that have not.

This balanced division of the dataset is critical for the model used in training to accurately distinguish between fire-affected and burned areas in forested and unaffected areas. As shown in Table 1, the dataset is divided into three subsets; this separation allows the model to be effectively trained on a variety of samples while achieving higher accuracy rates on the test data.

Table 1
Train, validation, and test distribution in dataset.

Set	Class	Original Count	Augmented Count (Estimated)
Training	fire	608	19456
Training	nofire	608	19456
Validation	fire	152	0
Validation	nofire	152	0
Testing	fire	190	0
Testing	nofire	190	0

Augmentation was performed here because the number of data in the dataset is not sufficient for the ResNet architecture and would lead to overfitting of the model. Initially, 20% of the training data was reserved for validation. As shown in Fig. 2, augmentation was then applied at each step of the training: horizontal rotation of the images, random zooming, and certain cropping operations were applied separately for each data in the dataset. For the test data, the data was only scaled to "1./255". Applying the augmentation to the test data may not reflect the real performance of the model and may lead to misleading results.

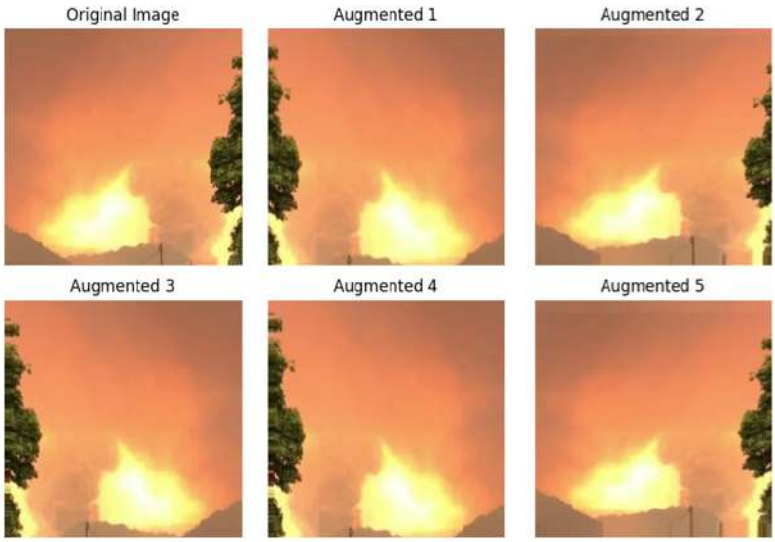

Figure 2: Augmentation example.

3.2. ResNet50v2 Model Architecture

Convolutional Neural Networks (CNNs) are among the fundamental building blocks of DL methods, and they're popular in tasks such as image and computer vision [24]. CNNs are based on extracting local features from high-order inputs and passing them to lower layers for more complex features [25]. This process allows the model to learn and achieve more accurate results. However, CNNs frequently tend to have issues training deeper, especially in deep networks. This is where deep network architectures like ResNet50v2 can provide a solution. ResNet50v2 is a member of the Residual Networks family and adds an important innovation to the traditional structure of CNNs: residual or jump connections [26]. These structures help solve the problem of gradient loss as the depth of the network increases.

Using ResNet50V2 architecture involves opting for residual blocks which helps to bypass the issues of vanishing and exploding gradient problems during deep representation learning. The purpose of this residual block is captured in an equation that includes the image to be processed, pre-trained weights corresponding to the YOLO CNN, and skip connections. This method is superior at producing results when there are variations in dimension [27]. Furthermore a solution to the degradation is provided using DL framework where the mapping of the layer of the non-linear stack is treated as a ‘cut’ from the original input.

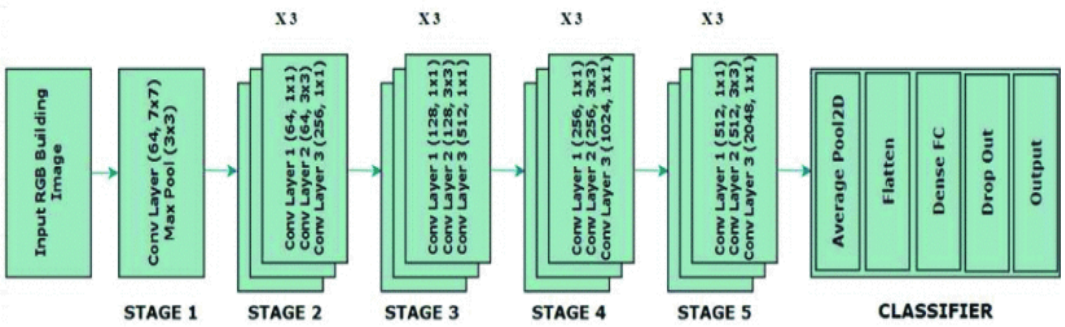

Figure 3: ResNet50v2 architecture.

The application of ResNet to computer vision has shown outstanding performance [28]. ResNet18, ResNet50, and ResNet101 are the most widely used types of ResNet networks. Among these network types, ResNet50 has achieved better identification accuracy and real-time performance [29]. The number 50 in its name represents the 50 layers that make up the ResNet50v2 architecture. These layers include the convolutional layer, the batch normalization layer, and the ReLU activation function [30].

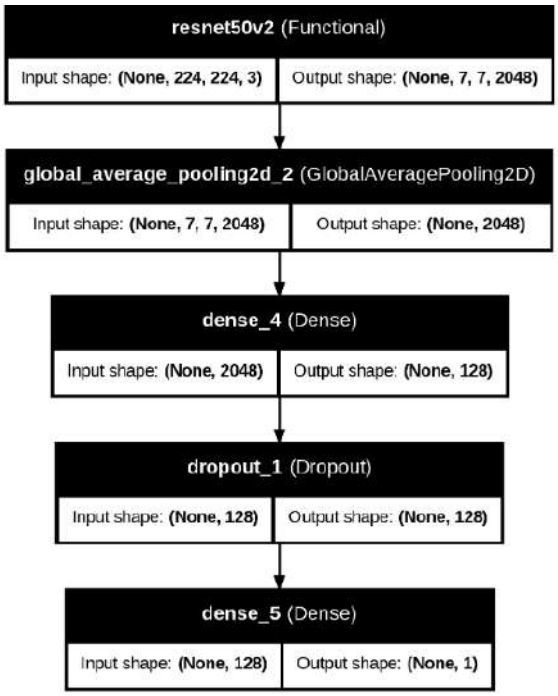

Figure 4: ResNet50v2 model architecture.

In this paper, the transfer learning method of the ResNet50v2 model is used to implement a DL model using the Keras library. In order for the model to efficiently extract features from the input data, ResNet50v2 is used as the base feature extractor with pre-trained weights on the ImageNet dataset. The model is loaded with a structure that excludes the classification headers, allowing only feature extraction. The architecture of the model as illustrated in Fig. 3, is built on top of ResNet50v2 as the base feature extractor and enriched with Global Average Pooling and Fully Connected (Dense) layers. This allows for a more compact feature set, greatly reducing the number of parameters required. The goal at this stage was to remove unnecessary complexity from the model.

The model is completed with Global Average Pooling and Fully Connected (Dense) layers. Global Average Pooling takes the average value of each feature map to create a more compact summary vector and reduce the number of parameters. This step increased the efficiency of the model. The resulting vector was transferred to a 128-neuron dense layer, where the risk of overfitting was reduced using the ReLU activation function and L2 regularization. In addition, a dropout layer was added and applied at 50% to increase the generalizability of the model. The output layer is built to perform binary classification using a sigmoid activation function and represents the model's classification decision as a value between 0 and 1.

4. Experimental Results

In this work, the ResNet50v2 model was transformed into a transfer learning model that was trained on a dataset defined as a forest fire detection dataset. The data was cleaned with fire and non-fire images in an equally weighted ratio. To increase variability and prevent overfitting in the data augmentation stage, random horizontal rotation, zooming, and cropping were applied during the training set hours to allow variability while ensuring that overfitting is contained. The validation and test sets did not require augmentation, although the test set was normalized to a range of 1/255.

The model was then modified to have a global mean pooling layer, a fully connected layer consisting of 128 neurons, an L2 regularization term with $\lambda = 0.01$, and a drop of 50%. The binary classification output layer had a sigmoid activation function reflecting the probability of firing. Training was done with the Adam optimizer. The learning rate was set to 0.0001 and the binary cross entropy loss was used. Early stopping was implemented to track accuracy loss, and training was terminated after observing 10 consecutive epochs in which there was no improvement.

Most academic research evaluates model performance not by a single measure, but rather by a combination of measures, including accuracy (1), recall (2), precision (3), and F1-score (4). These metrics allow for fair and comprehensive comparisons across tasks, in addition to providing a quantitative measure of model performance [32].

$$Accuracy = \frac{True\ Positive(TP) + True\ Negative(TN)}{True\ Positive(TP) + True\ Negative(TN) + False\ Positive(FP) + False\ Negat} \quad (1)$$

,

$$Recall = \frac{True\ Positives(TP)}{True\ Positives(TP) + False\ Negatives(FN)}, \quad (2)$$

$$Precision = \frac{True\ Positives(TP)}{True\ Positives(TP) + False\ Positives(FP)}, \quad (3)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

Table 2 presents the performance metrics of the model on the test data. The model performed well with an accuracy of 97.63%. This means that 97.63% of the samples tested were correctly classified. In addition, the precision of the model is 98.40%, meaning that 98.40% of all samples predicted to be fire were in fact correctly classified as fire. The recall rate is 96.84%, which means that most of the images containing fire are correctly recognized. The F1-score of the model is 97.61%, which is an important performance measure that reflects both the accuracy and the recall of the model in a balanced way. Overall, the model shows a high success rate and effective classification performance, with both false positives and negatives minimized.

Table 2
Model performance metrics on test data.

Metric	Value
Accuracy	97.63%
Precision	98.40%
Recall	96.84%
F1_Score	97.61%

There is a need to analyze the working of the model in a detailed manner, which can be done by analyzing certain different parameters. One of these metrics can be a confusion matrix as shown in Fig. 3. The confusion matrix protocol allows the user to more accurately determine the type of classes that have been solved compared to the others. In this way, it can be determined which fire class was correctly recognized and which was more prone to errors.

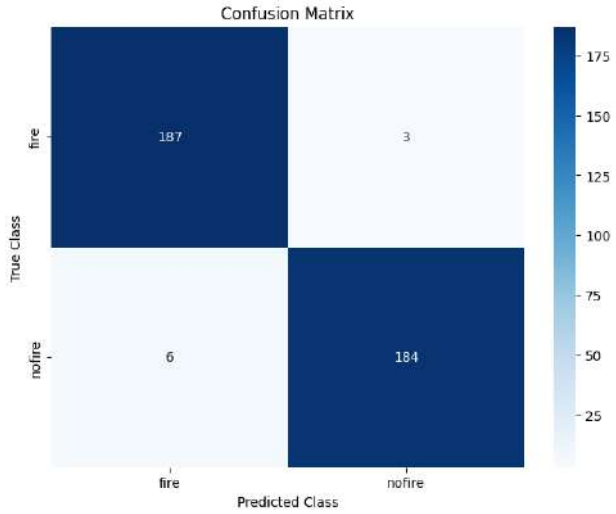

Figure 5: Confusion matrix of the model's fire classification.

5. Discussion

This article demonstrates a useful case of DL application for an important ecological problem: detecting wildfires. Applying the ResNet50V2 architecture together with small but cleverly augmented dataset results in 97.63\% accuracy and 98.40\% precision in locating wildfire affected regions from satellite images. With regard to transfer learning, the use of already trained ImageNet weights is one of the most notable advantages, as it allows for better results and faster convergence even when there isn't sufficient training data available. Data augmentation methods like horizontal flips, zooms, and crops help control overfitting, which is a serious problem when working with small datasets. Regularization techniques also improve the model's generalizability.

Still, the error analysis section would improve by providing more detail outside of the confusion matrix analysis. Determining if the true miss-classifications are false positives (areas without fire but marked as fire) or false negatives (burned areas that should have been marked but are not) is the most important part misclassification analysis. Examining those misclassified images could show the flaws in the model and the biases it holds.

Although many researchers use the ResNet50V2 architecture with transfer learning for image classification, our research is different. We customize the model to detect post-wildfire land damage using satellite images, an area not previously investigated. Unlike most prior work on real-time fire or smoke detection, our focus is on identifying areas of fire damage in forests. Moreover, unlike other more sophisticated solutions such as the dual-agent detection system described in [22], our model is less complicated while achieving the same high accuracy, thus better tailored for environments with constrained resources. To address the problem of limited datasets, we applied specific augmentation strategies, dropout, and L2 regularization. These methods help ensure robustness and generalization. The modular architecture and training pipeline enhance central and edge-based fire monitoring practicality.

Furthermore, examining the practical aspects of the proposed methods would greatly increase the impact of the study. For example, in what ways could this model be used with current wildfire monitoring systems? What are the implications for safeguarding the environment, saving money, and improving response time? Trying to answer these questions would reiterate the importance of the topic while enhancing the discussion providently.

6. Conclusion

Using the ResNet50V2 architecture, the model achieved a remarkable accuracy of 97.63% when classifying satellite images into wildfire and non-wildfire categories. The model's accuracy, coupled with its capacity to spot forest fires, makes it an invaluable asset for prompt fire detection and prevention. Adopting an approach based on DL and satellite imagery provides the opportunity to enhance the detection of fires' earliest stages, thus enabling quicker, more efficient actions. In addition, these real-time assessments can aid in firefighting efforts on a personal and communal level.

The use of satellite information for instant evaluation can have supportive implications in helping onlookers assess the location of fire activity. This is important in determining the location to dispatch firefighting teams to, hence optimizing resource use and reducing damage.

In addition, this study helps refine the general approach to managing forest fires. As the current version of the model improves, further steps can look into testing other augmentation strategies to increase the model's strength, new fine-tuning adjustments to improve performance, or even other neural network designs that are better intended for certain satellite images or regions geography. Such changes would greatly improve the range of applications of the model so that it can be configured to work in varying environmental and geographical regions, including those that are untapped. This development may enhance the capacity to monitor and prevent wildfires in different ecosystems around the world.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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Transfer training tools and methods for diagnostic tasks

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Abstract

The research about implementation transfer learning in medical diagnostics is important because it allows to evaluate how well already trained neural networks can adapt to specific medical data. This helps to understand which architectures work best, how to improve diagnostic accuracy, and reduce the risk of false positives. In addition, such research contributes to the development of more reliable and interpretable models, which is critical for physician confidence and the implementation of AI in real-world clinical practice.

Keywords

Machine learning, transfer training, medical diagnosis, artificial neural network, accuracy

1. Introduction

Transfer machine learning (TML) can be useful for training analytical diagnostic models as a basis for medical diagnostics, as it allows you to use already pre-trained models (models after the parametric synthesis stage) on new, similar tasks, reducing the need for large amounts of data. In medicine, even modern medicine, there is often a lack of large annotated data sets – usually, this applies to rare diseases, or viral (less often bacterial) infections that have passed the stage of seasonal or qualitative mutation, or diseases at the beginning of the epidemic (as was the case with COVID-19, for example) [1]–[3]. That is why the ability to adapt knowledge from other industries or similar tasks is very valuable. For example, models trained on a large general set of medical images can be further trained on smaller specific data sets for a specific diagnosis, which improves accuracy and reduces development time. This is especially important in radiology, where the analysis of CT, MRI, or X-ray images can be improved using models that have already learned to recognize common pathologies. It also reduces the risk of retraining, since the basic characteristics of images or signals (for example, tissue features or anomaly patterns) have already been studied by the model before. Unlike the neuroevolution approach, which usually requires a large data set to synthesize a more universal model, the principle of TML is to adapt an existing model to a specific, narrower task. In addition, it can contribute to better generalization of models, allowing them to work on different sets of patients, even if they differ in demographic or technical parameters [3].

TML shows good results precisely when using deep neural networks (DNNs) because of their ability to automatically extract and summarize complex multi-level data features. DNNs consist of many layers, where most layers are layers with hidden neurons, each of which learns to recognize certain patterns – from the simplest (edges, textures, normal indicators) on the lower layers to more complex (shapes, objects, splashes, pathologies) on the higher ones. This makes it possible to reuse already trained layers without the need for training from scratch, which is crucial for tasks where access to large amounts of annotated medical data is limited [2]. Moreover, retraining or complete re-synthesis of DNN can be extremely complex and resource-intensive for a computing system, which is not sufficiently optimized due to the receipt of a small amount of new data (2).

This is particularly effective in areas such as medical image analysis (CT, MRI, X-ray), where the first layers of DNN trained on large shared datasets (such as ImageNet) can be used to recognize basic visual patterns, while only the last few layers are adapted to a specific task. This significantly reduces the need for computing resources and training time. In addition, this strategy helps to avoid re-

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learning on small sets of medical data, since the initial layers already contain generalized characteristics that are well transferred between similar tasks, because the dataset can contain updated data of either individual patients or a specific pathology that requires confirmation or refutation.

Another reason for effectiveness is the ability of DNN to work with nonlinear and complex relationships in data, which is important in medical diagnostic tasks where pathologies can have complex and variable manifestations. With TLM, high accuracy can be achieved even with relatively small data sets, making this approach practical and effective in real-world medical applications [1]–[3].

However, which DNN topologies to choose, which methods can help better teach a structurally synthesized model, how to adjust the metaparameters of methods, and, ultimately, whether such an approach is really optimized for medical diagnostics should be considered in this paper [1]–[3].

2. Related Works

Automation of medical diagnostics is the use of technologies, in particular data processing algorithms, machine learning and artificial intelligence, to partially or completely perform the process of detecting diseases and making diagnoses. This may include analyzing medical images (MRI, CT, X-rays), interpreting laboratory tests, recognizing symptoms based on electronic medical records, and even predicting disease risks [4]–[8].

It should be noted that work on automating decision-making in medical diagnostics has been underway for quite a long time, which is associated with a number of important current needs:

- speed up the diagnostic process-automatic systems can significantly speed up the analysis of a patient's set of clinical indicators, which is critical in acute conditions (for example, stroke, heart attack), especially if you correctly configure the online transmission of clinical indicators after, for example, the actual analysis to the general system [1]–[7];
- improved accuracy – artificial intelligence (AI) techniques can detect patterns and non-obvious connections that a person may miss, even in an ultra-large data stream, reducing the risk of false or missed diagnoses;
- reduce the burden on doctors – automation helps reduce the share of routine work of doctors, giving doctors more time for complex clinical cases and communication with patients;
- increased access to health care – in the event of a shortage of qualified specialists in the regions or problems with the departure of medical care to dangerous, restricted locations, automated systems can help compensate for this shortage by providing high-quality preliminary diagnostics, and signal the real need to attract qualified specialists to extraordinary cases [8];
- standardization of diagnostic solutions – reducing the influence of the human factor allows you to minimize the variability in diagnosis between different doctors.

Therefore, it is necessary to clearly distinguish between the role of AI in the processes of such automation – AI is a key component of automation, since it is able to:

- process and analyze large amounts of medical data – images, tests, medical histories;
- recognize complex patterns and correlations that are difficult to detect even for experienced doctors [6]-[8];
- learn from previous cases-constantly improving the accuracy of predictions and diagnoses;
- perform routine tasks, such as sorting cases by risk level or automatically collecting patient data.

In general, AI does not replace doctors, but acts as a tool that enhances their capabilities, helping them make informed decisions and improve the quality of medical services.

The TML approach has a number of key advantages over classical machine learning methods, which is especially important in medical diagnostics. Therefore, TML has less need for large data sets– classical ML models require a large amount of annotated medical data to learn from scratch. Since collecting and labeling such data in medicine is complex and resource-intensive, transfer training allows you to use already trained models, adapting them to a specific task.

On the other hand, faster adaptation to new tasks. Learning from scratch (especially in DNN) requires a lot of time and computing resources. TML allows you to shorten this process by reusing the basic characteristics you have already learned [8].

In addition, the resulting neuromodels are better generalizability – DNNs trained on large shared data sets already contain knowledge of common features of images or signals, which makes them more resistant to changes in data than models trained only on specific medical sets.

The derived advantage of using TML is to reduce the risk of retraining – in classical approaches, when training on small medical datasets, the model can remember the features of a specific set (whether it is a specific group of patients, a specific disease, or even a specific patient), rather than learn general patterns. Thanks to transfer training, the basic levels of the network already contain generalized knowledge, which makes the adapted model more resistant to various variations in medical data. As already noted, learning DNN from scratch requires powerful hardware. TML reduces the need for long-term training and allows you to achieve high accuracy even on less powerful systems, thereby increasing the efficiency of using computing resources. Also, the TML approach has a certain versatility: the same approach can be used for various medical tasks: analysis of X-rays, CT, MRI, diagnostics using electrocardiograms or histological images.

Thus, TML is significantly more efficient than classical methods, as it allows you to adapt existing models to medical diagnostic tasks faster, more accurately and with less resource costs.

To clearly demonstrate this, let's look at a comparison table of different ML approaches for our problem of automating medical diagnostics in the form of a Table 1.

Table 1
Comparison of classical ML approaches with TML

Criteria	Transfer machine learning	Transfer machine learning
Need for data	Smaller, uses already trained models	Smaller, uses already trained models
Training time	Shorter, because it adapts already trained models	Shorter, because it adapts already trained models
Requirements for computing resources	Less, because mostly only the last layers are taught	Less, because mostly only the last layers are taught
Generalization of knowledge	Better yet, the basic features are already learned on large sets	Better yet, the basic features are already learned on large sets
Risk of overfitting	Lower, because the model already has general knowledge	Lower, because the model already has general knowledge
Flexibility in use	High-can be adapted for various medical tasks	High-can be adapted for various medical tasks
Application examples	Analysis of X-rays, CT, MRI, histology, ECG, pathology recognition	Analysis of X-rays, CT, MRI, histology, ECG, pathology recognition
Accuracy	Higher, especially for small data sets	Higher, especially for small data sets
Practical effectiveness	High-faster implementation in clinical practice	High-faster implementation in clinical practice

Transfer training is more effective for medical diagnostics when access to large amounts of data is limited and deployment speed is critical. Classical machine learning is useful when it is possible to build a large, high-quality dataset and train the model for a specific task.

To date, a number of independent and professional researches [9]-[14] have already been conducted on the introduction of TML technologies in medical diagnostics. TML involves using the knowledge gained by the model when solving one problem to improve results on another, often similar problem. This approach is particularly useful in medicine, where there is a limited amount of data to train models [7].

After analyzing a set of studies, we can conclude the general advantages of using TML in medicine, among which the researchers identified:

- resource savings: models pre-trained on large shared data sets can be adapted to specific medical tasks with less time and data.;

- improved accuracy: adapting models to medical data can lead to higher diagnostic accuracy, even with a limited amount of specific medical data.
- However, it should also be noted the general disadvantages and risks associated with the implementation of TML in medical diagnostics:
- risk of transferring inappropriate characteristics: if the baseline model was trained on data that is significantly different from medical data, this may lead to the transfer of inappropriate or undesirable characteristics, which will worsen the quality of diagnosis;
- interpretation problems: machine learning models, including those that use TML, can be black boxes, making it difficult to understand the reasons for making certain decisions that are crucial in medical practice;
- need for thorough validation: it is necessary to carefully test adapted models on medical data to ensure their reliability and accuracy before implementing them in clinical practice.

Overall, while TML offers significant benefits for medical diagnosis, it is important to consider potential risks and limitations while ensuring that models are thoroughly validated and adapted to the specifics of medical data.

As already noted, within the framework of this work, it is extremely important for us to deal with a number of issues related to the implementation of transfer training in medical diagnostics, namely: which DNN topologies to choose; which methods can help to better teach the structurally synthesized model; how to configure the metaparameters of methods. A similar research structure should be argued [.

Choosing a deep neural network (DNN) topology for transfer learning, configuring metaparameters, and learning methods are critical aspects when it comes to applying machine learning technologies to medical diagnostics. Here are some important points that explain why this is so important and how you can improve your results.

2.1.1. Selecting the DNN topology for transfer training.

The network topology (or architecture or structural structure) is crucial because it determines how the neuromodel will process data. For medical tasks, such as image diagnostics or analysis of medical records, architectures that are well-suited for image processing are most commonly used [15]:

- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN)
- Transformer-based models (most often for sequential data).

The choice of topology affects:

- model performance: an incorrect topology may cause the model to fail to learn or process data efficiently;
- generalization capability and quality: it is important that the network can transfer the acquired knowledge to new medical tasks without losing accuracy;
- model complexity: for small medical data sets, simpler models can be more efficient than complex ones that require huge amounts of data [16].

2.1.2. Methods for improving the training of a structurally synthesized model

In order to train the model more effectively, the following methods are used:

- Fine-tuning: this is the process in which a network pre-trained on a large amount of shared data adapts to a specific medical task. This method allows you to preserve the knowledge gained at the previous stage of training, and only partially retrain the model on new data [11];
- Data augmentation: in cases where medical data is limited, you can use data augmentation techniques to artificially enlarge the data set, creating new examples from the original ones through transformations (rotation, shifting, image scaling, etc.);
- Regularization: regularization techniques such as Dropout or L2 regularization help prevent overfitting, which is especially important when there is not enough data for training [12].

2.1.3. Configuring metaparameters

Among the metaparameters (or hyperparameters for some methods) of methods for training structurally synthesized models, there are [5]:

- learning rate: it is important to adjust the learning rate correctly so that the model does not get stuck in local lows or learn too slowly [15];
- batch size: the batch size determines how many examples will be processed before updating the scale. This can affect the stability and speed of learning;
- number of epochs: the number of iterations (epochs) of training in which the network adapts to data is an important factor for achieving optimal results.

Transfer training can be a good (if not the best) approach to implementing ML in medical diagnostics in general, given the frequent problem of data limitations, because the medical field often lacks large data sets to train models from scratch. TML allows you to use already trained models, which significantly reduces the need for data and time. Moreover, since decisions often need to be made quickly in medicine, the use of models pre-trained on large sets of General Data allows you to achieve results faster, and therefore solutions based on the use of the TML approach differ in speed and efficiency. It is also worth paying attention to the fact that transfer training allows you to effectively adapt General models to specific tasks related, for example, to rare diseases or specific medical images. Thus, TML will help increase the adaptability of neuromodels. [16]

However, this approach also has its own risks, especially if the adaptation of the model to new medical data has not been properly performed. It is important that the validation performed is thorough and takes into account the specifics of specific medical data, otherwise there is a risk of incorrect diagnoses.

Transfer training has great potential for medical diagnostics due to its ability to effectively use limited data and reduce training time. However, it is important to carefully choose the network architecture, configure metaparameters, and take into account the specifics of medical data to achieve optimal results [17].

3. Materials and the methods

As noted earlier, DNN networks are most often used for the TML approach. Quite often, among medical clinical data, you can find visualized test results, for example: X-rays, or MRI or CT. Then the diagnostic task is a more complex task of computer vision – image recognition. That is why among all possible topologies of DNN networks, we will choose those topologies that best demonstrate themselves in working with images, namely: CNN, DenseNet, VGG16, ResNet and InceptionNet [18]-[20]. For clarity, we will compare all the considered topologies in the form of a table: Table.2.

The CNN architecture is one of the most common architectures for image processing. It consists of several layers:

- convolutional layers: key components for identifying image features such as contours, textures, etc.;
- pooling layers: reduce image size while maintaining important features;
- fully connected layers: exit at the last stage for classification or regression.

Overall, CNNs are highly efficient in image recognition due to their ability to process spatial structures.

DenseNet or Densely Connected Convolutional Networks): this is an improved version of CNN, where each layer has direct connections to all previous layer [18]s. This allows the model to have more context and make better use of information from previous stages. Compared to conventional CNNs, increased learning efficiency is most often noted due to the reduction of the problem of gradient attenuation and improved accuracy due to the stronger exchange of information between layers.

VGG16 or Visual Geometry group 16: this is a deep CNN with 16 layers. It uses small filters (3x3) and large layers for more accurate feature detection. Of course, this architecture is easy to implement and learn thanks to the use of the same filters (3x3) in all layers [19].

The ResNet architecture uses the concept of skip connections, which allows you to skip certain layers and avoid the problem of fading gradients when training deep networks. It can work effectively with very deep networks (up to several hundred layers). And the structural feature improves learning

ability by using redundant links that allow you to skip multiple layers without losing important information [20].

Table 2
Comparison of DNN topologies

Characteristics	CNN	DenseNet	VGG 16	ResNet	InceptionNet
Architecture	Base layers with convolution and pooling	Tightly connected layers	Deep CNN with 16 layers	Skip connections	Inception blocks with different filters
Network depth	Usually 10-30 layers	Usually 100-200 layers	16 layers	High (can reach hundreds of layers)	Many depth options depending on the configuration
Main advantage	Easy and efficient image processing	Improved learning thanks to thick connections	Simplicity, works well with small data	Skip layers (skip connections) for deep networks	Higher efficiency thanks to the use of various filters
Disadvantages	May have problems with deep networks	It can be difficult to calculate due to the large number of parameters	Large volumes of parameters, which can be a problem for memory	It can be difficult to train with a lot of parameters	Optimization is required to reduce parameters
Learning speed	Moderate	Slower due to the large number of parameters	Fast training thanks to the simplicity of the architecture	The right setup for an effective workout	High thanks to the combination of different filters
Application in medicine	Diagnostics of medical images, pathology analysis	High-precision image classification	Diagnostics of images with small details	Analysis of complex medical images	Wide real-time application for image analysis

InceptionNet (GoogleNet): this is an architecture that includes the concept of Inception blocks, where filters of different sizes (1x1, 3x3, 5x5) are used for each layer in order to preserve a variety of functions. It differs in that it increases efficiency and reduces the number of parameters by combining filters of different sizes. Well adapted for real-time use [19].

We will use dropout as the basis of transfer training. Dropout is a regularization technique used in DNN to prevent overfitting. It randomly shuts down a certain percentage of neurons during training, which forces the model not to depend on individual neurons and process information more universally. In the context of transfer training, dropout can be used to improve the efficiency and stability of the model [18].

In TML, we often have a model pre-trained on a large set of General Data, and then adapt it to specific data (for example, medical images). Enabling dropout during adaptation reduces the risk of retraining on new data, especially if the amount of data is limited [18].

During fine-tuning, when we adapt an already trained model to a specific task (for example, classification of medical images), dropout helps to avoid over-training on a small data set. This ensures that the model does not remember specific features of training data, but can summarize new examples [20].

TML often involves using models that have been trained on large shared data sets and then adapted to a narrow, specific task (such as detecting specific diseases in medical images). Because new data

may be less representative or have fewer examples, dropout helps reduce the likelihood that the model will remember insignificant or noisy data that can cause diagnostic errors [19].

TML often experiments with different dropout values (for example, 0.3-0.5), depending on the task and data availability. Too high a dropout can make learning more difficult, while too low a dropout will not give the desired regularization effect.

4. Experiment

A sample of data on patients with Pneumonia from the Mayo Clinic's Article was selected for the experiment [21].

Images from the entire sample for the experiment will be redistributed as follows, as in Table.3.

Table 3
Data distribution between experiment stages

Train set	
Pneumonia	3875
Normal	1341
Test set	
Pneumonia	390
Normal	234
Validation set	
Pneumonia	8
Normal	8

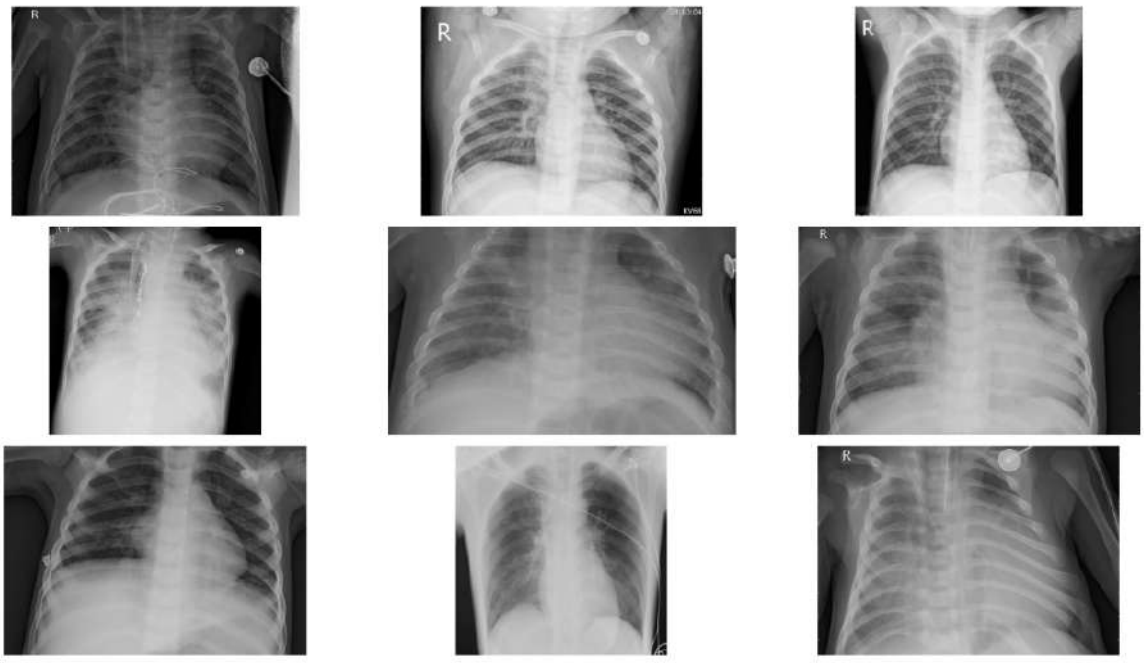

Figure 1: Example of images from a dataset

For all topologies, we define the following training metaparameters: Table. 4

Table 4
Table title

Metaparameter	Value
The number of epochs	10
Batch size	8+1+1
Detect that feature (activation function)	using the ReLU activation

The accuracy of all solutions demonstrates in the Table 5.

Table 5
Data distribution between experiment stages

Neuromodel	Train Accuracy	Test Accuracy
CNN	89.69%	84.62%
DenseNet	92.45%	84.46%
VGG 16	61.81%	65.71%
ResNet	81.96%	81.73%
InceptionNet	69.04%	70.51%

The following Fig.5-6 show the dynamics of changes in diagnostic accuracy.

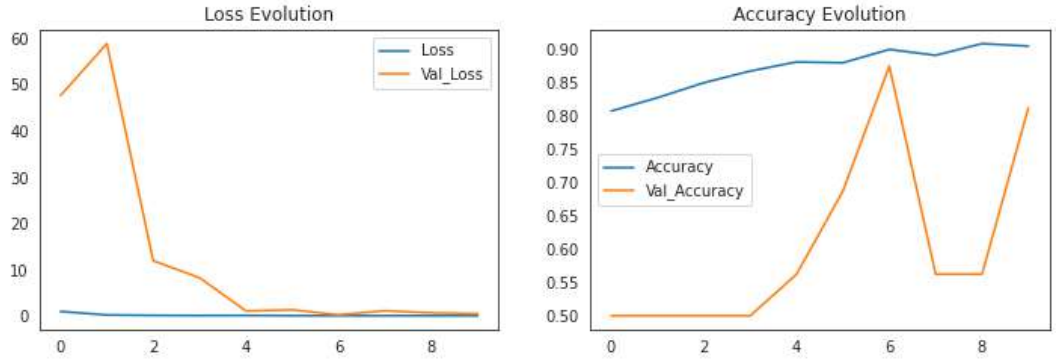

Figure 2: The dynamics of changes in diagnostic accuracy for CNN neuromodel

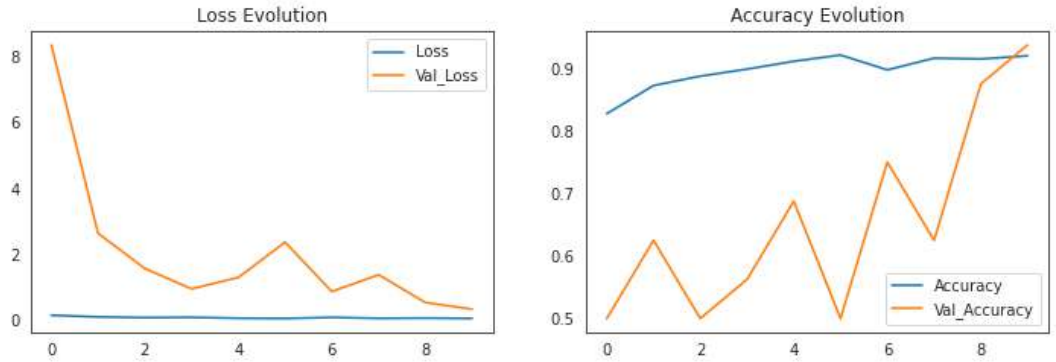

Figure 3: The dynamics of changes in diagnostic accuracy for DenseNet neuromodel

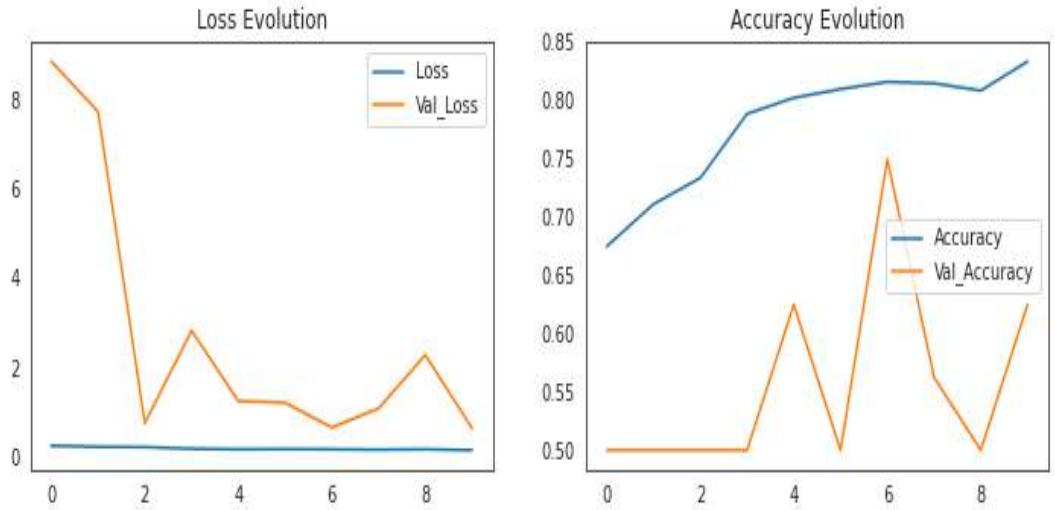

Figure 4: The dynamics of changes in diagnostic accuracy for VGG 16 neuromodel

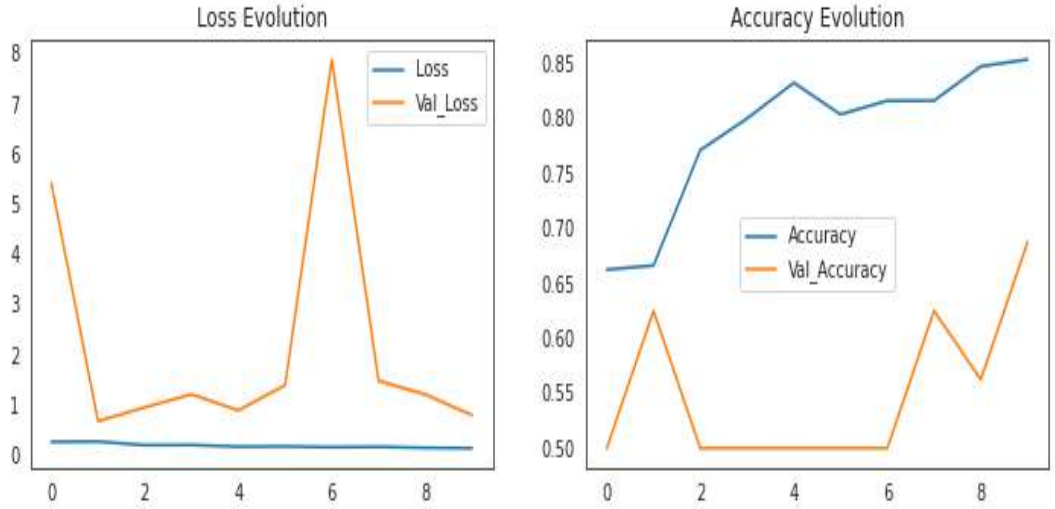

Figure 5: The dynamics of changes in diagnostic accuracy for ResNet neuromodel

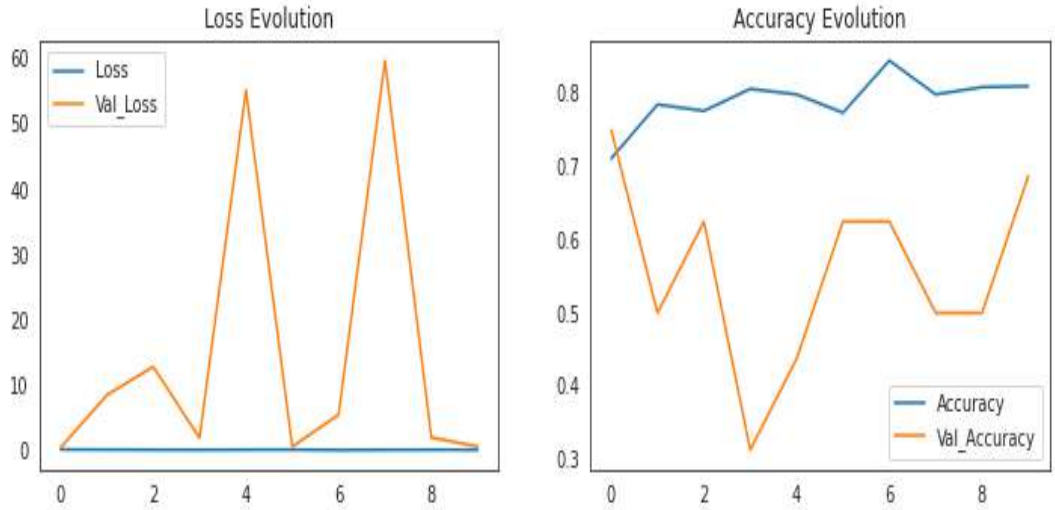

Figure 6: The dynamics of changes in diagnostic accuracy for InceptionNet neuromodel

5. Analysis of results

The analysis of the results should begin with noting the striking difference in accuracy between classical CNNs and all other types of DNNs. Most notably, the difference is not even 10-15%.

There are several possible explanations for why CNNs performed better in X-ray image classification compared to more advanced architectures such as DenseNet, VGG16, ResNet, and InceptionNet.

Firstly, it is simplicity of structure and lack of parameter overload. More modern architectures, such as ResNet or DenseNet, contain a large number of parameters and complex mechanisms that are optimized for processing very deep and complex images, such as ImageNet. X-ray images typically have fewer high-level texture features, so simpler CNNs can learn more efficiently without the risk of overfitting.

Secondly, it is limited variability in X-ray images. Unlike natural images (with huge variations in textures, colors, and objects), X-ray images have a similar structure and fewer unique features to extract. Conventional CNNs can quickly learn to extract the necessary medical features without the need for complex mechanisms like ResNet (residual connections) or DenseNet (dense layer connectivity).

Moreover, retraining and data requirements. Deep networks like ResNet or InceptionNet require very large amounts of data to train effectively. If your X-ray dataset is not large enough, then deeper architectures may not reach their maximum efficiency and may need to be retrained.

Further, artifacts and noise in medical images. Deeper architectures may be more sensitive to artifacts, noise, or contrast variations in X-ray images. Conventional CNNs, due to their simplicity, can learn to ignore unnecessary details and focus only on key patterns.

Finally, model optimization and adaptation. Some modern architectures are optimized for color or more variable images, while X-rays are usually black and white (grayscale). This can lead to inefficient use of many filters in large networks. Limitations in hardware resources

More complex networks require significantly more computing resources for inference. If the system used for training and testing had limited capabilities (e.g., weaker GPUs or limited memory), this could affect the performance of complex architectures.

6. Conclusion

For image-based medical diagnoses, each of these architectures has its advantages. CNN is a classic and efficient method, suitable for basic tasks. DenseNet and ResNet provide better deep network processing capability and reduce training problems, so they are suitable for more complex medical images. VGG16 is a great option for simple but accurate tasks. InceptionNet is optimal for reducing the number of parameters and improving efficiency, which is important for real-world medical applications.

Benefits of using transfer learning and dropout, in particular:

Reduced overfitting: The model becomes less prone to overfitting on new data, which is especially important when working with small medical datasets.

Improved generalization: Thanks to regularization, the model can better generalize knowledge and transfer it to new, previously unknown examples.

Improved learning stability: Combined with fine-tuning techniques, dropout helps the model consistently achieve optimal results without large fluctuations in performance on validation data.

Dropout is a useful technique for transfer learning, especially when adapting models to specific tasks with limited data, such as medical diagnosis. By using dropout during fine-tuning, you can effectively reduce the risks of overfitting and improve the model's ability to generalize to new examples.

Transfer learning has a great future in medical diagnostics, as it allows to effectively use knowledge from large datasets to analyze X-ray, CT, or MRI images, even when annotated medical data is limited. This significantly reduces training time and improves the quality of predictions, especially if the models are adapted to the specifics of medical images.

However, it is important to keep in mind that standard architectures trained on ImageNet are not always optimal for medical tasks, so they should be modified to take into account specific data features. In general, transfer learning is a promising approach that has already demonstrated success in clinical practice, but requires careful validation and adaptation to specific medical cases.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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