Improved Generative Adversarial Network and Particle Swarm Optimization Support Vector Machine for Tennis Serving Behavior Analysis

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Keywords: video images, generate adversarial networks, particle swarm optimization algorithm, support vector machine, behavior analysis

Received: October 9, 2024

This study proposes a behavior analysis model based on an improved generative adversarial network and particle swarm optimization support vector machine algorithm for deblurring and feature extraction in tennis video serving behavior. The model first improves the generative adduction network by introducing a multi-layer convolution structure and a variety of activation functions, including three-layer convolution. The activation function is selected to use ReLU and Leaky ReLU alternately to enhance the generator in capturing image details. During model training, the generator optimizes the output image by minimizing the Wasserstein distance, and the discriminator evaluates the difference between the generated image and the real image. Then, to further extract features, the particle swarm optimization algorithm was used to dynamically optimize the feature extraction of each frame in the feature space, and dynamically adjust the inertia weights. The initial value was 0.9 and the final value was 0.4. After feature extraction, the data were input into SVM for classification. The penalty parameter of SVM was set to 1 and the accuracy was set to 0.001. The results of the comparative experiments demonstrated that the proposed method exhibited superior performance in deblurring images, with an average subjective score of 81.16 points, a notable advantage over the comparison algorithm. In the objective evaluation, the average Peak Signal-to-Noise Ratio (PSNR) and structural similarity value of the image after defuzzing by the research method reached 35.12dB and 0.93, respectively. The PSNR and structural similarity of the image increased by 13.56% to 18.29% and 8.33% to 19.90%, respectively. In the feature extraction and classification experiments, the accuracy of the proposed algorithm reached 91.24%, which was significantly higher than the traditional algorithm. The convergence speed was faster than the particle swarm optimization algorithm, the ant colony optimization algorithm, and the simulated annealing algorithm, reducing the number of iterations by 35.33%, 40.52%, and 51.55%, respectively. The data validate that the designed method has good application prospects in improving video image quality and feature extraction.

Povzetek: Raziskava se ukvarja z analizo teniškega servisa, ki z izboljšanimi algoritmi GAN in PSO-SVM poboljša ugotovitve iz slik.

1 Introduction

In light of the accelerated advancement of digital media and video technology, the analysis and processing of video content have become increasingly important in many fields. Especially in sports science and sports analysis, how to extract valuable information from video images has become a research focus. Tennis, as a dynamic and complex sport, often suffers from blurring in its video images due to various factors such as the athlete's rapid movement, different shooting angles, and changes in lighting. These factors can lead to a decrease in image quality, affecting game analysis and technical evaluation [1-2]. Therefore, improving the clarity and information extraction ability of Tennis Video Images (TVI) has important practical significance for athlete performance evaluation and tactical analysis [3-4]. Currently, many industry scholars have researched the image processing technology and action behavior analysis. Ding Q et al. proposed a camera-based long-term trajectory tracking technique to improve the effectiveness of multi-target tracking technology in sports game feature recognition. This study first improved the Tracking-Learning-Detection (TLD) algorithm and then integrated machine learning methods into the improved algorithm. This method has significantly improved performance and can be effectively applied to feature extraction in sports events [5]. Mulimani D et al. developed a video preprocessing technique under a new framework. This method first calibrated players and classified occlusions to ensure accurate identification of athletes in complex game environments. Subsequently, by utilizing the system to

track and label athletes on the court, the framework significantly improved the tracking accuracy of basketball players and provided more reliable technical support for fairness in the game [6]. Zhang J et al. developed a new spatial attention and temporal dilation GCN that uses a self-attention mechanism to select human joints that are beneficial for action recognition, thereby reducing the impact of data redundancy and noise. Extensive experiments on NTU-RGB+D and Kinetics Skeleton have shown that this method completes State-of-the-art (SOTA) performance in skeleton-based action recognition [7]. Zhu X et al. introduced a skeleton attention module in the action recognition data system, which shoots the skeleton sequence onto a single-RGB frame to assist focusing on the limb motion area. Experiments on the NTU RGB+D and SYSU benchmarks have shown that compared to SOTA methods, this model achieved competitive performance while reducing network complexity [8]. The results of related work are summarized in Table 1.

While the aforementioned research has yielded promising outcomes in the domains of video image processing and action

Table 1: Research status analysis

Method	Accuracy (%)	PSNR (dB)	SSIM	Major deficiency
Ding Q et al. [5]	82	28.5	0.76	Multi-target tracking accuracy is insufficient in complex background.
Mulimani D et al. [6]	80.5	29	0.79	The real-time and accuracy of rapidly changing scenes are insufficient.
Zhang J et al. [7]	86	30.8	0.82	Data redundancy and noise are likely to affect the processing of diverse actions.
Zhu X et al. [8]	84	31.1	0.81	The recognition ability in complex motion scenes needs to be improved.

behavior analysis, it has not yet fully addressed the intricacies of the fuzzy states that arise in motion scenes. When faced with information redundancy and feature overlap, it is easy to encounter the problem of misidentification of action behavior. This study aims to propose a method based on the combination of improved a Generative Adversarial Network (GAN) and Particle Swarm Optimization - Support Vector Machine (PSO-SVM) for fuzzy removal and feature extraction in TVI processing. The innovation of this method lies in combining improved GAN and PSO algorithms to optimize the overall process of deblurring and feature extraction, making it suitable for complex motion scenes. By dynamically adjusting the inertia weight, the convergence speed and accuracy of the PSO algorithm have been improved, effectively enhancing the performance of the model at the feature extraction level.

2 Methods and materials

2.1 Deblurring processing based on video images

The goal of this research is to propose a method based on the combination of improved GAN and PSO-SVM to improve the deblurring effect and feature extraction ability of TVIs, thereby improving the accuracy of tennis serve motion recognition. The research specifically focuses on solving the problem of image blur and information redundancy caused by dynamic scenes. Assuming that the improved GAN structure will effectively enhance feature extraction capability through multi-layer convolution and multiple activation functions. Therefore, the goal of improving Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) indicators, and achieving more accurate recognition of tennis serving actions can be achieved. The analysis of tennis serve movements is not only important for improving athletes' technical level but also has significant implications in sports training, match judgment, and tactical development. Therefore, this study is expected to provide effective support for sports science and intelligent sports applications.

Tennis is a popular competitive sport, divided into singles and doubles forms. Participants throw the ball and hit it with a racket to make it land on the opponent's court. In tennis matches, serving is the way the game begins and an important part that determines the pace and strategy of the game. Serving is a highly technical action in tennis that involves multiple key elements, including preparation, pitching, hitting, and swinging. Serving is not only a technical action but also a strategic behavior. Athletes can choose different types of serve and make different choices based on their opponents' weaknesses and court conditions. Choosing which side of the court to serve on can affect the opponent's receiving angle and preparation. When

serving, the athlete's psychological state can also affect their performance. At the same time, the serving behavior of athletes is influenced by various factors, including physical fitness, proficiency in serving skills, the athlete's judgment of the game progress, understanding of the opponent, and scientific training methods and feedback mechanisms. In terms of physical fitness, technical proficiency, and tactical awareness, athletes need to continuously improve through their own efforts. In terms of scientific training methods and feedback mechanisms, this study believes that using video image processing technology can provide a detailed analysis of athletes' serving movements. By capturing the athlete's serve process at a high frame rate, analyzing the movements in great detail, and using computer vision algorithms to process the video, it is possible to extract keyframes, measured serve angles, speeds, and technical elements. By using machine learning to analyze serving data, patterns and performance characteristics of athletes during training can be identified.

The occurrence of blurry video images in TVI can be attributed to a number of factors, including the camera's shutter speed being inadequate to capture fast-moving objects during rapid motion, such as the swing of a racket or the trajectory of a ball. The shaking or vibration of the shooting equipment can cause the entire image to blur. Shooting tennis matches in low light environments can also increase the risk of motion blur [9]. The fuzzy model of TVI can be represented by equation (1).

$$I_B = K * I_S + N \tag{1}$$

In equation (1), I_B is the blurred image, which is the object that needs to be restored or studied during the analysis process. I_S is the original image, which represents the true state of the athlete at the moment of serving. By restoring the original image, the serving behavior can be analyzed more accurately. K is the convolution kernel. In serve analysis, convolutional kernels can be used to simulate the trajectory of an athlete's swing and ball flight, aiming to understand the source of ambiguity. N is additive noise, which may be interference caused by device noise or changes in ambient light. Analyzing this noise can improve the accuracy and reliability of serving moments. * is a convolution operation. In the analysis of serving behavior, this operation helps identify and simulate the cause of blurring, thereby restoring the original image and analyzing the behavior. In the context of blurry images, the Camera Response Function (CRF) is an important tool. It helps to understand and process image data by describing how the camera converts light into image pixel values, as given by equation (2) [10].

$$g(I_{S(i)}) = I_{S'(i)}^{\gamma} \tag{2}$$

In equation (2), g is the CRF approximation function, which describes the conversion of light rays into pixel values. The significance of CRF lies in its capacity to rectify discrepancies in image brightness resulting from disparate camera models or shooting conditions, thereby enhancing image uniformity and comparability. γ is a constant value, usually set to 2.2 by default. $I_{S(i)}$ is a potential clear image, representing the original unaffected image. It is an ideal image that can be generated through deblurring and restoration, thereby helping to establish accurate feature representations in image retrieval. $I_{S'(i)}$ is a clear image observed. The calculation of blurred image I_B is shown in equation (3).

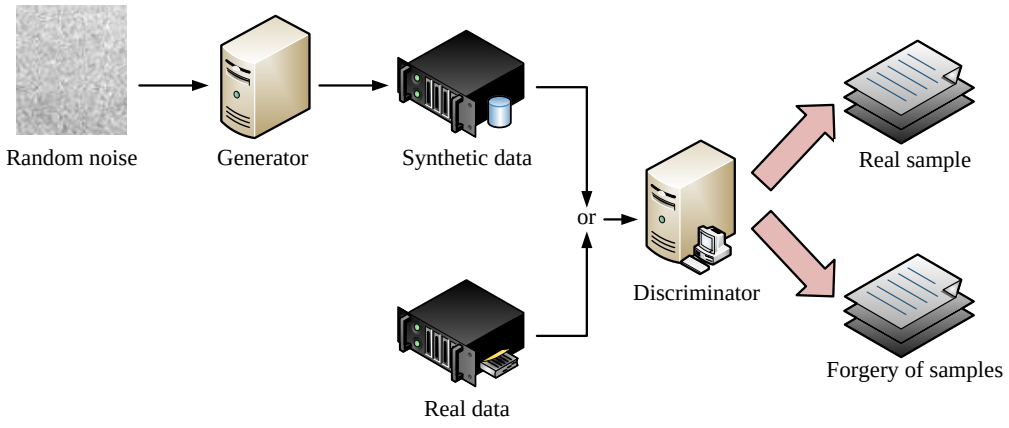

Figure 1: GAN structure.

$$I_B = g(\frac{1}{M}\sum_{t=1}^{M} I_{S(t)}) \quad (3)$$

In equation (3), t is the time in the video image. M is the number of clear frames used to generate blurry images. In image retrieval, the quantity of M affects the quality of blurry images. Collecting multiple clear images can help generate more stable and rich image features. This study calculates the actual blurred image using equation (4).

$$I_B = g(\frac{1}{T}\int_{t=0}^{T} I_{S(t)} dt) \quad (4)$$

In equation (4), T is the exposure time period, which indicates the reception time of the light line in the captured image. In image retrieval, the corresponding exposure time can affect the brightness and details of the image. This study adopts a non-blind deblurring method for blurry images. This method can obtain information about the blur kernel used in the restoration process of blurred images. The blur kernels may be the result of a number of factors, including camera motion, object motion, inaccurate focusing, and other causes [11-12]. This study assumes that the noisy and original images are Y and X, and the blur kernel stands for Z. The non-blind deblurring process is given by equation (5).

$$\left\{\hat{X}, \hat{Z}\right\} = \arg\min \left\| Z \otimes X - Y \right\|_2^2 + \varphi(X) + \theta(Z) \quad (5)$$

In equation (5), $\varphi(X)$ is the regularization term for the expected clear image. $\theta(Z)$ represents possible fuzzy kernels. Due to the excellent performance of GAN, this study applies it to denoising sports images. Figure 1 shows the GAN structure.

In Figure 1, the task of the GAN generator is to receive blurry images as input and attempt to generate outputs corresponding to real clear images. The generator gradually adjusts its parameters by learning the mapping relationship between blurry and clear images to achieve the goal of generating high-quality clear images. At the same time, the discriminator receives the image and outputs a probability value representing the probability that the input image is "real". The discriminator strives to improve its judgment ability to accurately identify the differences between the generator's output and the real image [13-15]. The objective function for the confrontation between the generator and discriminator is shown in equation (6)

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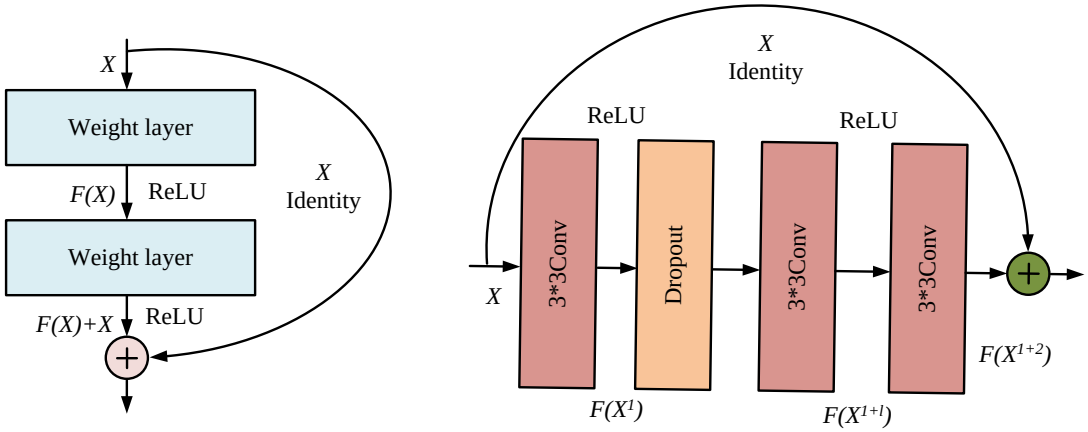
$$\min_G \max_D V(D,G) = E_{x\sim P_{data(x)}}[\log D(x)] + E_{z\sim P_{z(z)}}[\log(1 - D(G(z)))] \quad (6)$$

In equation (6), x is a real sample from $P_{data(x)}$ used to train the discriminator and help it learn how to recognize the characteristics of clear images. $E_{x\sim P_{data(x)}}$ is the expectation for



(a) Traditional residual block structure diagram

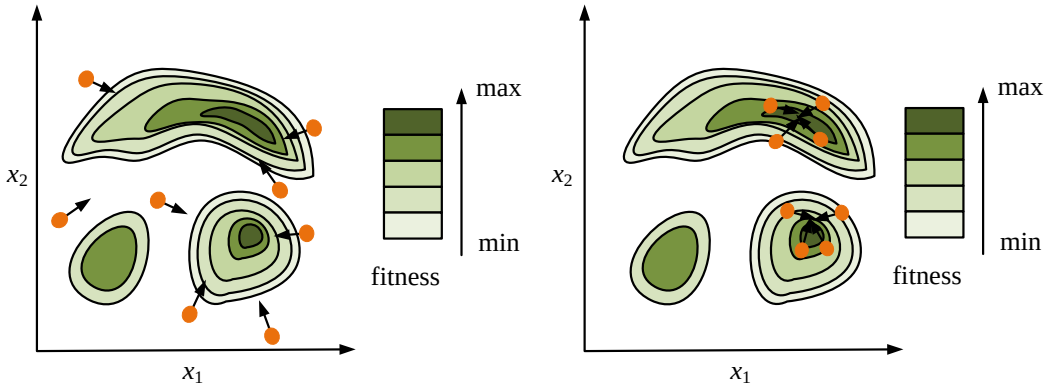
(b) Structure diagram of improved residual block

Figure 2: Traditional residual block structure.

clear input images. In the field of image retrieval, the concept of "expectation" plays a pivotal role in the development of effective models. By effectively calculating expectations, a more balanced approach to generation and discrimination can be achieved, ultimately enhancing the clarity and quality of both

generated and blurred images. $D(\cdot)$ is the output of discriminator D. The discriminator continuously optimizes its classification ability by comparing real samples with generated samples. In image retrieval, the performance of the discriminator affects the quality of the generated images by the generator, which further affects the accuracy of the retrieval results. $G(\cdot)$ is the output of generator G. When the image retrieval system faces a fuzzy query, the generator can transform the fuzzy image into a clear image. Wasserstein GAN (WGAN) is a variant of GAN. In image deblurring tasks, gradient vanishing is a common problem due to image degradation and other reasons, which affects the convergence of the model. This study uses Wasserstein distance to quantify the difference between the generator and the real data distribution, which can better handle the problem of gradient vanishing and help the generator learn the data distribution better [16]. To improve the deblurring effect of images, this study improves the structure of traditional residual blocks. The Residual Bock Structure (RBS) is displayed in Figure 2.

In Figure 2 (a), RBS extracts feature from the input blurred image through multiple convolutional layers. For TVI, important features include the trajectory of the ball and the movements of the athletes. Meanwhile, with the help of residual connections, the network can converge to the optimal solution faster. However, traditional residual blocks typically contain fewer convolutional layers or simpler structures, which may limit the model's capacity to learn complex features and details. In the face of more complex models, the lack of effective regularization may lead to overfitting. Therefore, this study improves the traditional RBS, as shown in Figure 2 (b). The improvement of residual blocks in this study mainly includes increasing the depth of convolutional layers, introducing multiple activation functions, applying Dropout, implementing skip connection modules, and removing batch normalization. The improved residual block consists of three convolutional layers, each using a 3x3 convolution kernel. This design enhances the expressive power of



(a) time 1 (a) time 2

Figure 3: Schematic diagram of PSO particle motion.

the model, enabling it to capture more complex feature representations. Introducing two ReLU activation functions between two convolutional layers can accelerate convergence and help the model learn nonlinear features. The final skip connection module is retained to alleviate gradient vanishing and explosion problems, ensure the flow of important information, and maintain the training stability of the model. Removing the batch normalization layer makes the model more flexible during small batch training and reduces computational burden. The loss function is shown in equation (7).

$$W(P_{data}, P_g) = \inf_{\gamma \sim \prod(P_{data}, P_g)} E_{(x,y)\sim\gamma}\left[\|x-y\|\right] \quad (7)$$

In equation (7), x and y are real samples and generated samples. In image retrieval, real samples are the basis for training network models. Generating samples is the key to successful high-quality image retrieval. $\prod(P_{data}, P_g)$ is the set of joint distributions of P_{data} and P_g. By comparing the joint distribution of real samples and generated samples, the generator can more effectively capture the features of real data when generating images, ensuring the similarity between generated samples and real samples in the feature space. $(x, y) \sim \gamma$ is one of the samples, which supports adversarial training between the generator and

discriminator, improving the model's generalization ability and optimization performance. $\inf$ is the expected distance. The loss function of the model generator is equation (8).

$$L_x = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} \left(\begin{matrix} \Phi_{i,j}(I^S)_{x,y} \\ -\Phi_{i,j}(G_{\theta G}(I^B))_{x,y} \end{matrix} \right)^2 \quad (8)$$

In equation (8), $\Phi_{i,j}$ is a feature map that can capture important semantic information and high-level features in the image. $W_{i,j}$ and $H_{i,j}$ are the width and height of the feature map.

2.2 Feature extraction and classification of video images based on PSO-SVM algorithm

The above study extracts and recognizes key features of video images by improving the residual network structure. Due to the complexity of dynamic scenes in tennis, video images often contain a large amount of information, resulting in the problem of information redundancy between features, which has a negative impact on feature extraction. To improve the effectiveness of feature extraction, this study introduces PSO-SVM [17-18] into the model. In the PSO-SVM algorithm, PSO is responsible for feature extraction in tennis, while SVM is responsible for feature recognition and classification. In PSO, individuals update their position and velocity to find the optima to the problem. The concept of employing PSO for the purpose of extracting features from motion images entails the treatment of each frame within the image sequence as a particle. Through the optimization of the particle's motion trajectory, it is possible to selectively capture salient features of object motion [19]. The PSO motion is shown in Figure 3.

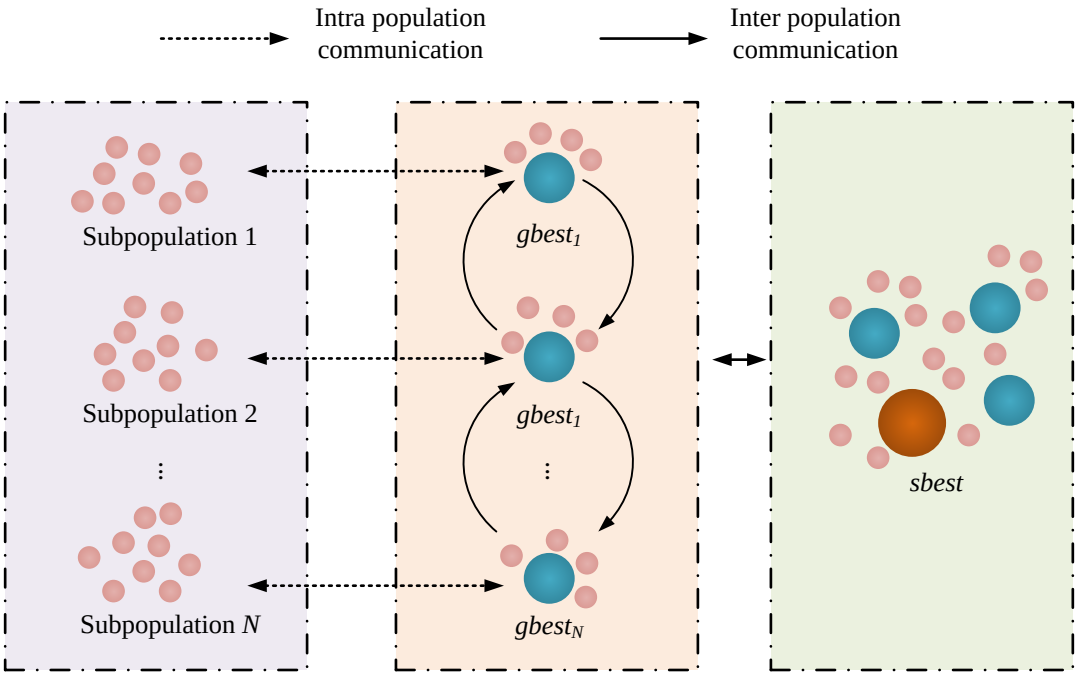


Figure 4: MPSO structure diagram.

Figure 3 shows the motion of PSO particles. In the initial stage of the PSO, a set of particles is generated at random, each representing a possible solution value. The motion of each particle mainly updates its current position and velocity. After each update, the fitness of each particle's current position is calculated to evaluate the quality of that position. The particle speed update is shown in equation (9) [20].

$$V_i^{t+1} = \omega \times V_i^t + c_1 \times rand() \times (pbest_i - X_i^t) + c_2 \times rand() \times (gbest - X_i^t) \quad (9)$$

In equation (9), ω is the inertia weight, which is usually a non-negative value. c_1 and c_2 are acceleration factors. The position of the i-th particle is represented as vector X_i. $rand()$ represents a random number between [0, 1]. $pbest_i$ is the optimal

position of particle i. The best position of the population is represented by $gbest$. When the ω value is large, the global Search Ability (SA) is strong and the local SA is weak. When the ω value is low, the local SA is strong and the global SA is weak. The expression for particle position is shown in equation (10).

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{10}$$

The above process indicates that the PSO owns the characteristics of simplicity, ease of implementation, and strong universality. However, due to the fact that particles in PSO belong to the same population, it is easy to form local optimal positions, resulting in the inability to obtain global optimal solutions and the problem of excessive dependence on

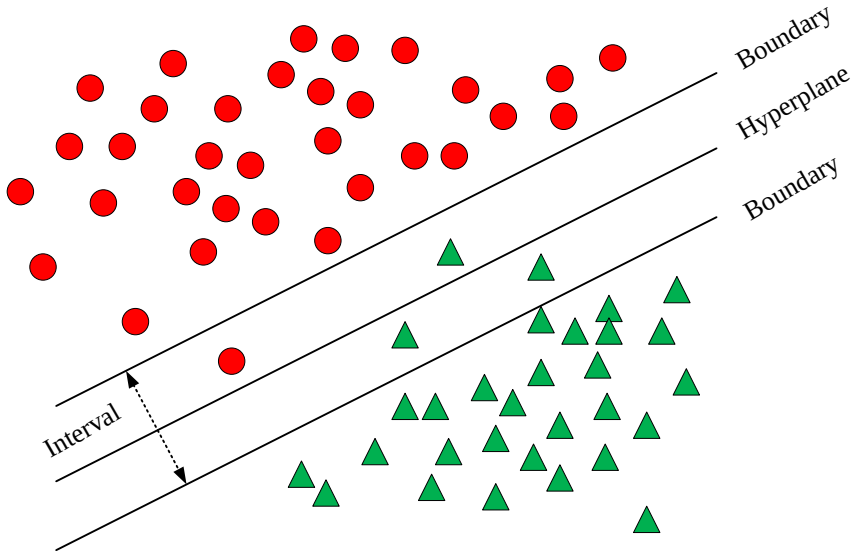


Figure 5: SVM optimal classification hyperplane.

parameters. In response to the above issues, this study adopts a combination of multiple groups and adaptive adjustment of acceleration coefficients to optimize PSO and proposes the MPSO optimization algorithm [21-22]. The MPSO algorithm can effectively improve the division of labor and cooperation among populations. In MPSO, a population contains multiple sub-populations, which in turn contain multiple particles. The MPSO algorithm structure is shown in Figure 4.

In Figure 4, each sub-population is a complete communication and interaction system. All particles within the population can communicate. During algorithm iteration, it is required to discover the optimum $gbest$ for each subgroup, and then find the optimal solution $sbest$ for the entire particle swarm, which is $sbest = \max(gbest_1, gbest_2, ..., gbest_N)$. N is the number of sub-populations. Therefore, in MPSO, the velocity update formula for particles is shown in equation (11).

$$V_i^{t+1} = \omega \times V_{id}^t + c_1 \times rand() \times (pbest_{id}^t - X_{id}^t) + c_2 \times rand() [\lambda (gbest_{kd}^t - X_{id}^t) + \theta (1-\lambda)(sbest_d^t - X_{id}^t)] \tag{11}$$

In equation (11), ω is the inertia weight. $pbest_{id}^t$ and $sbest_{id}^t$ are the historical and global best position of particle i and particle swarm. $pbest_{kd}^t$ is the optimal position of sub-population k so far. c_1, c_2 are the acceleration factors. $rand()$ is a random number between [0, 1]. λ is the classification accuracy of the sample. θ is the number of sub-populations. Due to the impact of inertia weight on the balance of local and global SAs, the value of inertia weight is crucial in PSO algorithm. However, the control effect of fixed inertia weights on global and local search capabilities is limited. Accordingly, this study employs a linear differential descent method to dynamically adjust the inertia weight, thereby enhancing the algorithm's overall SA in the initial stage of iteration and enhancing its local SA in the subsequent phase of iteration. The dynamically adjusted inertia weight is shown in equation (12).

$$\omega(t) = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) * t^2}{t_{\max}^2} \quad (12)$$

In equation (12), t is the current iteration count. $t_{\max}$ is the maximum iterations. $\omega_{\max}$ is the initial inertia weight, which is set to 0.9 in the study. $\omega_{\min}$ is the inertia weight at the maximum iteration count, set to 0.4. The improved particle velocity update formula is shown in equation (13).

$$V_i^{t+1} = \omega(t) \times V_{id}^t + c_1 \times rand() \times (pbest_{id}^t - X_{id}^t) + c_2 \times rand()[\lambda(gbest_{kd}^t - X_{id}^t) + \theta(1-\lambda)(sbest_d^t - X_{id}^t)] \quad (13)$$

In equation (13), $\omega(t)$ is the dynamically adjusted inertia weight. The above is a feature model construction built on the improved PSO. The MPSO first randomly divides the particle swarm into K sub-populations and initializes the sub-population particles randomly. Then, the individual extremum of the particles, the optimal value of each sub-population, and the global optima of the entire PSO are selected. The next step is to determine the optimal value found in the search. If the conditions are met, running is stopped. Otherwise, the speed and location of the particles are continued to update, and the best value is selected to continue running the algorithm until the conditions are met. Finally, the optimal solution of the optimization problem is outputted. After extracting features from video images as described above, this study uses SVM for feature recognition and classification [23-25]. SVM is an algorithm that maps low dimensional data to high-dimensional data to minimize functional. The model is defined as shown in Figure 5.

In Figure 5, SVM is a binary classification model. This model is the nonlinear classifier with the largest interval in the feature space. The learning strategy of SVM is to maximize the interval, which can be formalized as a convex quadratic programming problem. This is equivalent to the minimization problem of a regularized hinge loss function [26-27]. The learning algorithm of SVM is the optimization algorithm for solving convex quadratic programming. This study assumes a sample size of (x_i, y_i). x_i is the input vector. y_i is the corresponding output target. The SVM model initially employs a high-dimensional mapping feature space, which facilitates the identification of a superior hyperplane for the separation of diverse categories of data. Subsequently, it utilizes linear functions within the feature space for function approximation. According to statistical theory, the SVM minimum optimization objective function yields a fitted regression function as shown in equation (14) [28].

$$\min(W, b) : \frac{1}{2} W^2 + C \sum_{i=1}^{n} \left| y_i - [W, \varphi(X) - b] \right| \quad (14)$$

In equation (14), W is vector data. b is the function threshold. y is the function value after dot product processing. $\varphi(X)$ is an approximation function. C is the penalty coefficient for training model complexity and controlling model loss. The classification of the model can be completed through equation (14). This model can effectively solve problems regardless of the sample size or whether the linear fitting conditions are met, and due to its global strategy, it will not be unable to obtain the optimal solution due to local optima. In the PSO-SVM model, particles dynamically adjust their position and speed through interactions to efficiently capture features in video frames. Each particle represents a potential solution whose position corresponds to the selection of key attributes in feature extraction. The fitness value of the particle is evaluated based on the classification accuracy feedback. Additionally, the particle is able to learn which features are most relevant in tennis serve recognition by comparing with the historical optimal position and the global optimal position. The specific particle parameters, including inertial weights and acceleration factors, influence the exploration and development capabilities of particles, which assist in balancing global search and local search in complex feature spaces. Ultimately, this improves the accuracy and recognition rate of feature extraction.

3 Results

3.1 Analysis of deblurring effect based on video image processing and PSO-SVM

To verify the performance and effectiveness of the research algorithm, this study conducts comparative experiments for analysis. The comparative methods include GAN, Attention Mechanism-GAN (AGAN), and Multi-Scale Convolution (MSC) algorithm. In the improved GAN structure, the number of convolutional layers has been improved to enhance the extraction capability of intricate features. Each convolutional layer employs a 3×3 convolution kernel to facilitate the capture of image details with greater precision. In addition, ReLU and Leaky ReLU activation functions are used interchangeably, aiming to avoid the "dead neuron" phenomenon and improve the model's ability to learn from non-linear features. By removing batch normalization, the study enhances the flexibility of the generator and reduces the introduction of noise. It is imperative to ensure that each algorithm is configured with identical initial settings to minimize variation. Furthermore, the number of iterations must be trained up to 3,000 times. The learning rate of GAN is set to 0.0002. The learning rate of PSO is set to 0.5, and the number of PSO particles is 100. The initial value of inertia weight is 0.9 and dynamically adjusted to 0.4. The acceleration factor is set to 2.0. Performance evaluation indicators include relative subjective and objective indicators. The relative subjective indicator is the subject's evaluation of image quality. Objective indicators are selected as PSNR and SSIM. The higher the PSNR value, the closer the SSIM value is to 1, indicating

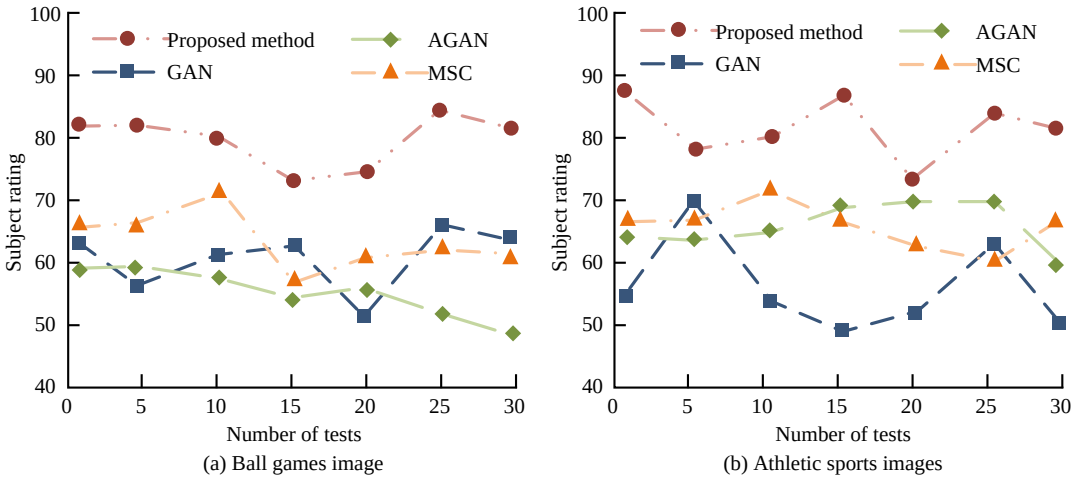


Figure 6: Subjective evaluation score results of the model.

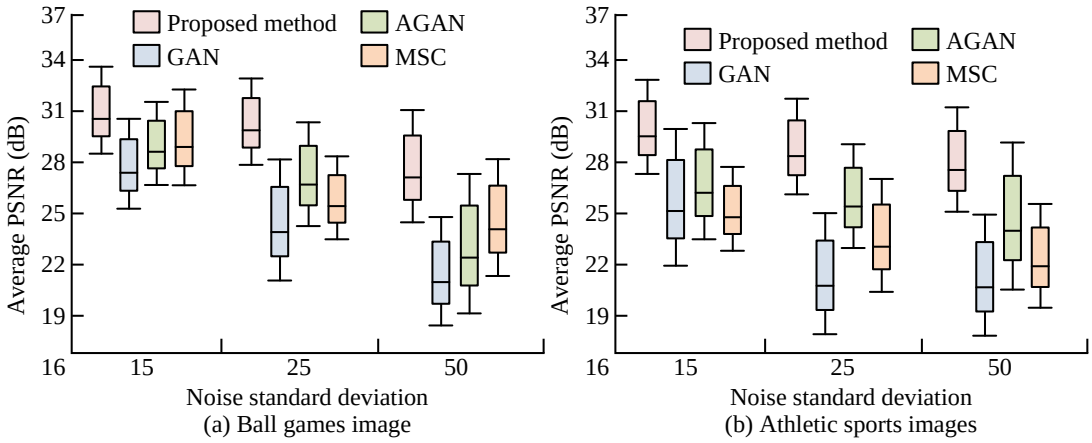


Figure 7: Comparison of average PSNR of different deflurring algorithms.

better image quality, that is, better deblurring effect. The experiment uses sports images from the GOPRO dataset for testing. This dataset divides images into ball sports and track and field sports. In subjective evaluation, the model score results are shown in Figure 6.

Figures 6 (a) and (b) show the subjective evaluation scores of subjects on the deblurring effect of images in ball sports and track and field sports. In Figure 6 (a), the deblurred image under the research method scores the highest, with an average score of 81.16 out of 30 experiments. In the evaluation of 50 subjects, the research method shows better deblurring effect on ball sports images. In Figure 6 (b), the subjective evaluation obtained by the research method is better, and the mean score of the deblurred image is 86.94. The average scores of AGAN, GAN, and MSC do not exceed 75. To compare the PSNR and SSIM performance, this paper adds noise with standard deviations of 15, 25, and 50 to the test original images, respectively, to generate test images for testing the algorithm's deblurring ability. Following the implementation of a research adjustment, the image quality has been markedly enhanced, as evidenced by elevated PSNR and SSIM values. This signifies that the generated image is more closely aligned with the authentic image in terms of structural similarity and clarity. It is particularly well-suited for the processing of dynamic motion scenes. Figure 7 is a boxplot of the mean PSNR of various algorithms.

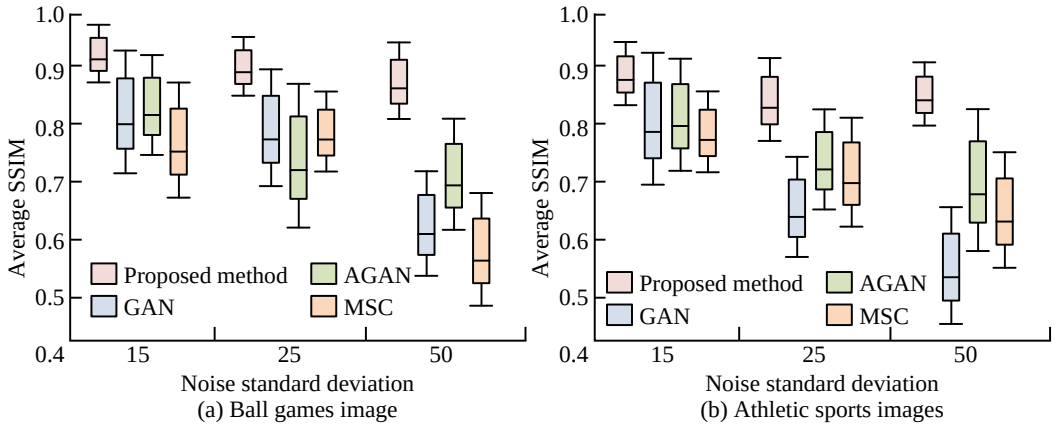


Figure 8: Average SSIM of different deblurring algorithms.

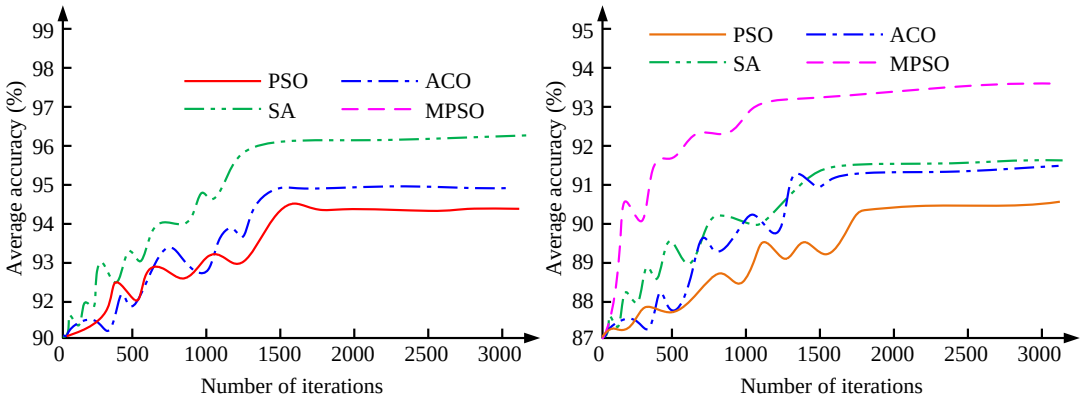
Figures 7 (a) and (b) show the average PSNR performance of algorithms in image deblurring tests for ball sports and track and field sports. The PSNR values of the research methods are consistently the highest. Compared with AGAN, MSC, and GAN, the research method increases the average PSNR by 13.56%, 15.02%, and 18.29% in Figure 7 (a), and by 12.82%, 14.02%, and 22.72% in Figure 7 (b), respectively. This indicates that the difference between the original and the deblurred images is smaller under the research method, indicating that the deblurring effect is better. Figure 8 shows the mean SSIM boxplots of four algorithms.

In the deblurring tests of ball sports and track and field sports images in Figures 8 (a) and (b), the SSIM values of the research method are the highest, and the overall performance is more stable. Compared with AGAN, MSC, and GAN algorithms, in Figure 8 (a), the average SSIM of the research method increases by 8.33%, 12.24%, and 19.90%, while in Figure 8 (b), it increases by 12.34%, 19.38%, and 22.20%. Overall, the research method has the best deblurring effect, followed by AGAN, MSC, and finally GAN. The experimental results validate the effectiveness of this study.

3.2 Feature extraction based on video image processing and PSO-SVM model

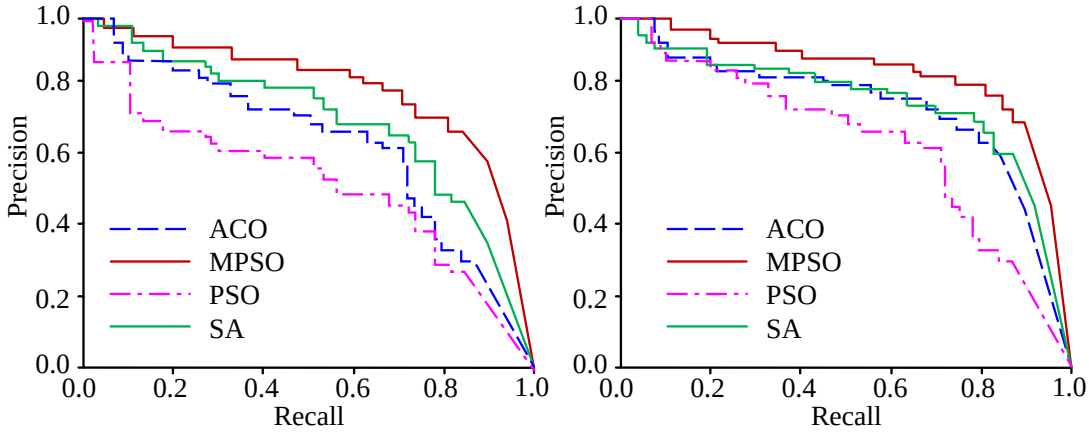
To validate the proposed sports image feature extraction algorithm, this study selects the difficult to solve single peak function Rosenbrock and the easy to trap algorithm in local optima multi-peak function Griebank as the standard test functions. To verify the convergence performance of MPSO, this study compares PSO, Ant Colony Optimization (ACO), and Simulated Annealing (SA). In the experiment, all algorithms are set with the same common parameters, namely population size and dimensionality. The iterations are 3000. Each algorithm is independently run 100 times on each test function, and statistical analysis is conducted on the results of the 100 runs. Figure 9 shows the convergence curve of the obtained algorithm.

Figure 9 shows the convergence curves of the algorithm on Griebank and Rosenbrock. MPSO achieves the highest average accuracy in the shortest number of iterations. In Figure 9 (a), at 850 iterations, MPSO approaches convergence with an average accuracy of 97.31%. Compared to the other three algorithms, MPSO has reduced the number of iterations during convergence by 35.33%,



(a) Test results on Griewank (b) Test results on Rosenbrock

Figure 9: Comparison of algorithm convergence curves.



(a) Ball game images (b) Athletic sports images

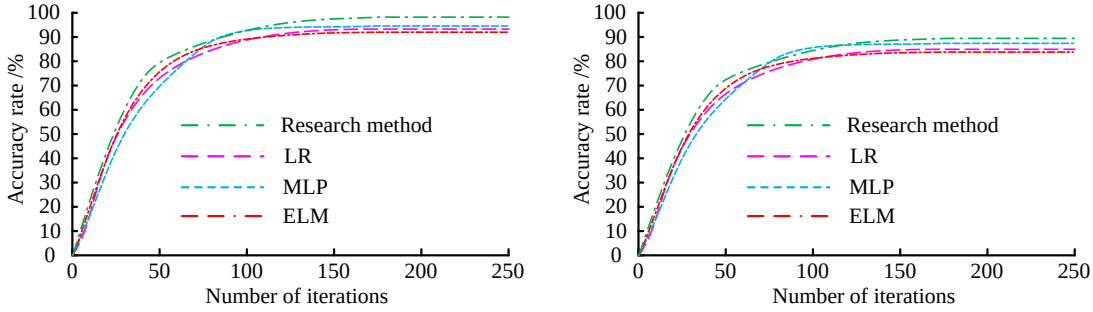
Figure 10: Comparison of algorithm PR curve.

40.52%, and 51.55%. In Figure 9 (b), after 1100 iterations, MPSO approaches convergence with an average accuracy of 92.94%. In contrast, the number of iterations during MPSO convergence decreases by 25.37%, 26.54%, and 41.89%. This verifies that the iteration speed and accuracy of MPSO are superior to SA, ACO, and PSO. To validate the performance of various feature extraction algorithms, this study tests the Precision-Recall (PR) curves of different algorithms, as exhibited in Figure 10.

Figure 10 shows the PR curves of various algorithms in the images of ball sports and track and field sports. In Figure 10 (a), the performance of each algorithm from best to worst is MPSO, SA, ACO, and PSO, respectively. In Figure 10 (b), MPSO has the best feature extraction performance, while ACO and SA have similar performance. ACO has the relatively worst feature extraction performance. Finally, in sports image feature extraction, feature extraction time is also a commonly used evaluation metric, which can be used to determine the efficiency of feature extraction methods.

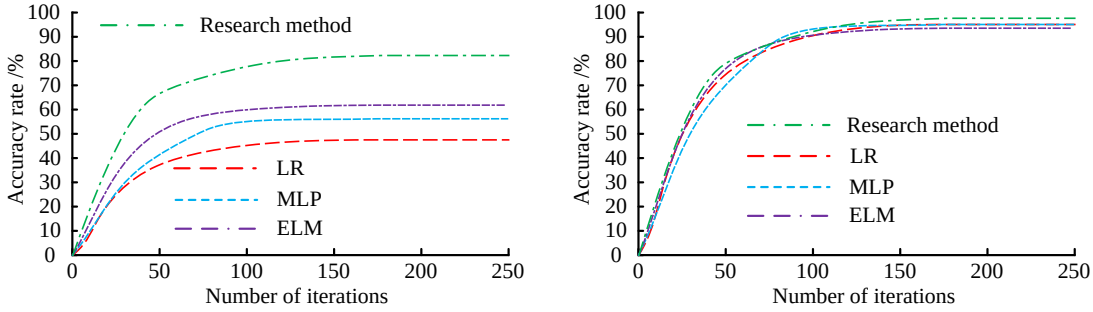
3.3 Behavior analysis based on video image processing and PSO-SVM Model

To verify the effectiveness of the research



(a) Prepare posture behavior analysis accuracy (b) Analysis accuracy of service swing action

Figure 11: Analysis accuracy of preparation posture and serving and swinging behavior.



(a) Batting action behavior analysis accuracy (b) With wave as behavior analysis accuracy

Figure 12: Accuracy analysis of hitting action and swing action behavior.

model in analyzing action behavior in video images, this study collects match videos of tennis players with a total length of 5.6 hours. This study categorizes the serving actions of tennis players in videos into five behaviors, including preparation posture, serving swing, hitting action, swing action, and recovery posture. This study sets the SVM related parameters, with a penalty coefficient of 1 and SVM error accuracy of 0.001. The experiment recognizes five types of actions and uses Logistic Regression (LR), Extreme Learning Machine (ELM), and Multi-Layer Perceptron (MLP) as comparison methods. The analysis results of the preparation posture and serve swing behavior are shown in Figure 11.

Figure 11 (a) shows the accuracy results of the "preparation posture" behavior analysis. The behavior analysis accuracy of the research algorithm has reached 97.2%, which is 5.84%, 7.62%, 8.04%, and 8.16% higher than LR, ELM, and MLP methods. Figure 11 (b) shows the accuracy results of the analysis of the "serve swing" behavior. The accuracy of the research algorithm reaches 90.4%, which is about 1% higher than MLP. This indicates that the comparative algorithm may have difficulty capturing complex motion features due to the limitations of its linear model, and may still be insufficient in capturing diverse and delicate features. The research method adopts advanced feature extraction techniques, which can better identify and classify a small number of posture changes. Figure 12 shows the accuracy analysis results of hitting and swinging movements in tennis serving behavior.

In Figure 12 (a), the behavior analysis accuracy of the research algorithm reaches 82.8%, which is 33.6% higher than LR, 20.8% higher than ELM, and 24.5% higher than MLP. In Figure 12 (b), the behavior analysis accuracy of all four methods reaches over 98%. Therefore,

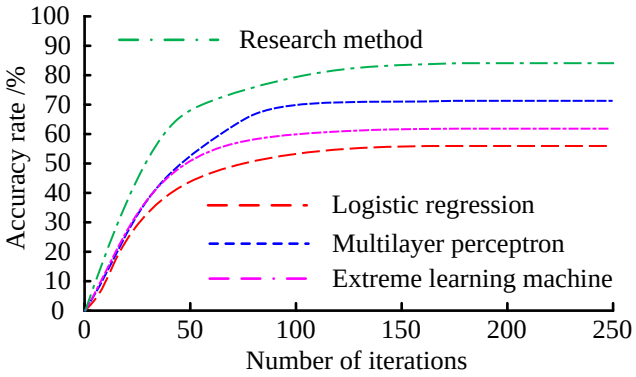


Figure 13: Accuracy of posture recovery behavior analysis.

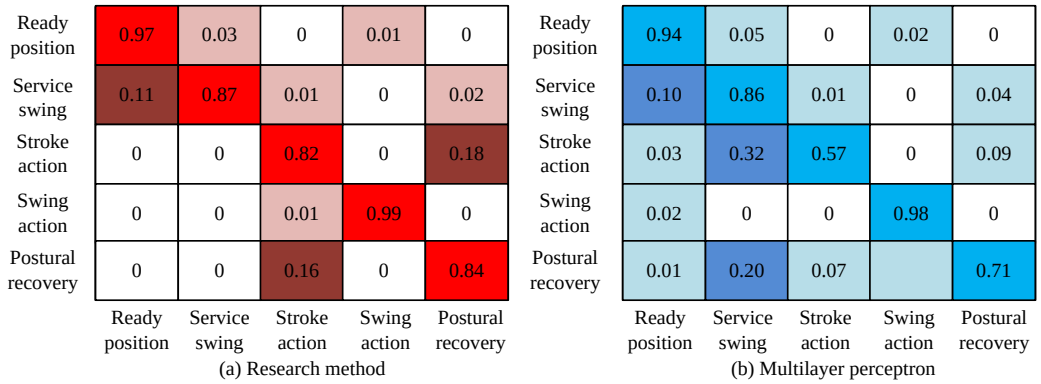


Figure 14: Confusion matrix results of different algorithms.

the research algorithm significantly improves the recognition ability of "hitting action", possibly due to its sensitivity to action details and dynamic changes. Figure 13 shows the accuracy results of posture recovery analysis in tennis serving behavior.

In Figure 13, the analysis accuracy of the research algorithm for "posture recovery" behavior reaches 84.7%, LR is 58.2%, ELM is 62.3%, and MLP is 70.3%. The research algorithm has obvious advantages in behavior analysis, indicating that it has better feature extraction and action classification performance. This study proposes methods to analyze the recognition performance of MLP, as shown in Figure 14.

Figure 14 shows the confusion matrix results of the research method and MLP. In Figure 14 (a), the overall recognition accuracy of the research method reaches 91.24%, and in the dynamic classification effect, the main manifestation is mutual interference. There is an 18% probability that the "hitting action" will be misidentified as "posture recovery". There is a 16% chance that the "posture recovery" action will be misidentified as a "hitting action". This shows that there is some overlap and confusion in the recognition between these two actions. This phenomenon may be attributed to the fact that the player's posture during the act of serving is analogous to that observed during the subsequent recovery phase. This results in an insufficient degree of feature extraction, which in turn hinders the ability to distinguish between the two movements. To reduce misclassification, it would be beneficial to consider optimizing the classifier threshold in SVM to adjust the decision boundary, thereby improving the ability to distinguish between these actions. In Figure 14 (b), the MLP method has lower recognition performance than the research method in dynamic actions. Although its dynamic actions have significant interference, the recognition accuracy of the research method is over 80%. This indicates that the research model owns good anti-interference ability and high recognition accuracy in action recognition. This study compares the computational efficiency of different models. The details are listed in Table 2, using model runtime, GPU usage, and memory usage as evaluation metrics.

Table 2: Comparison results of model calculation efficiency.

Algorithm	Run time (s)	GPU Usage (%)	Memory usage (MB)
Research method	45.2	75.3	512
AGAN	55.6	80.1	600
GAN	62.8	82.4	650
MSC	50.4	78.5	580
LR	40.1	72.0	500
ELM	42.3	71.5	490
MLP	43.0	73.2	495

In Table 2, the research method shows superior performance in terms of running time, significantly reducing computation time compared to other algorithms. Its GPU usage rate is 75.3%, which is relatively lower compared to algorithms such as AGAN and WGAN, indicating that the research model is more efficient in utilizing computing resources. In terms of memory usage, the research method has also shown good optimization ability, maintaining a usage of 512MB, which is reduced compared to other methods. To further reduce processing requirements, this study can implement effective memory management strategies to optimize the allocation of computing resources, thereby reducing memory consumption and improving computing speed. For example, small batch processing and dynamic memory allocation. These strategies not only improve the operational efficiency of the model but also ensure that good performance can be maintained when processing large-scale data. The research method is further compared with the Recurrent Neural Network (RNN) and Convolutional Neural Network Ensemble Long Short-term Memory Network (CNN-LSTM) models. The results are shown in Table 3.

The results in Table 3 show that the research method outperforms RNN and CNN-LSTM in several performance indexes. Specifically, the accuracy of the research method is as high as 91.24%, which is significantly higher than the 85.1% of RNN and 87.3% of CNN-LSTM. In terms of image quality, the PSNR and SSIM of the research method are 35.12 dB and 0.93, respectively, indicating a robust defuzziness effect and the capacity to preserve structural details. In comparison, the corresponding indexes of RNN and CNN-LSTM are 32.5 dB and 0.87, and 33.8 dB and 0.89, respectively. It shows that the latter is relatively weak in image quality. In addition, the research method has a relatively low runtime and memory usage (45.2s and 512MB), showing better computational efficiency. Overall, these results validate the advances in accuracy and efficiency of the research method, indicating its application potential in complex dynamic scenarios.

4 Discussion

When deblurring TVI, the average subjective score of the research method in the GOPRO dataset was 81.16 points, and the PSNR value increased by 13.56%, 15.02%, and 18.29% compared to AGAN, MSC, and traditional GAN. The potential benefit of studying the model lies in optimizing the adversarial learning mechanism between the generator and discriminator. This could result in the generator paying greater attention to image details and effectively reducing blurring phenomena. By introducing multiple convolutional layers and activation functions, the model's ability to learn complex features was enhanced, thereby improving the clarity and realism of generated images. This study demonstrated significant advantages in feature extraction using PSO-SVM. The accuracy of the MPSO algorithm reached 97.31%, and its convergence speed improved by 35.33%, 40.52%, and 51.55

Table 3: Comparative results of advanced nature

Method	Accuracy (%)	PSNR (dB)	SSIM	Run time (s)	GPU Usage (%)	Memory Usage (MB)
Research method	91.24	35.12	0.93	45.2	75.3	512
RNN	85.1	32.5	0.87	55.0	78.2	520
CNN-LSTM	87.3	33.8	0.89	50.5	76.5	510

% Compared to traditional PSO, ACO, and SA. The advantage of the research method lied in the introduction of multiple population PSO strategies, which enable different sub-populations to share information and optimal solutions. By using linear differential descent, the inertia weight of particles was dynamically adjusted, which could enhance the global SA in the early stage and local SA in the later stage, thus improving the stability and efficiency of the feature extraction process. In the action recognition experiment, the recognition accuracy of the research method reached 91.24%, and in feature recognition such as hitting action and posture recovery, it was higher than classical algorithms such as LR, ELM, and MLP. The recognition accuracy for the "preparation posture" behavior reached 97.2%, while the recognition accuracy for the "hitting action" was as high as 82.8%. By improving the residual network structure, the model could effectively extract deep dynamic features from action sequences, enhancing its ability to capture complex motion trajectories. This enabled the action classification model to more accurately identify various behaviors of different athletes. In similar studies, Frejus et al. proposed a behavior recognition model based on neural networks, which showed good recognition accuracy in posture recognition [29]. Luo Z et al. proposed a behavior recognition model grounded on multi-layer LSTM, which demonstrated good performance in specific applications [30]. However, the above research cannot effectively capture small differences between actions when dealing with complex dynamic sequences, which can easily lead to misidentification in similar actions. Compared with it, the research method can comprehensively handle complex dynamic scenes and has high flexibility and robustness, providing a new approach for motion behavior analysis.

In complex dynamic scenes, the recognition challenges of moving images are often caused by motion blur, background interference, and illumination changes. The proposed model shows good robustness in various complex situations, mainly due to the design of adaptive feature extraction and adversarial learning mechanism. The introduction of PSO algorithm makes the feature extraction process more flexible and adaptive. When dealing with dynamic scenes, the particle can dynamically adjust its position to capture the key movement trajectory of the player and the ball, which improves the relevance and usability of the feature. By optimizing the adversarial training process between generator and discriminator, the enhanced GAN model is capable of not only generating high-quality images but also of producing more robust mapping relationships in the feature extraction process. This mechanism serves to mitigate the impact of noise and background changes on the results, thereby enhancing the overall robustness of the model.

5 Conclusion

With the rapid growth of video technology, the processing and behavior analysis of TVI have become increasingly important. To address the challenges of video image blurring and feature extraction, this paper constructed a comprehensive method built on improved GAN and PSO-SVM algorithms. For fuzzy processing, the improved GAN significantly improved the ability to recover details through the introduction of multiple convolutional structures and various activation functions. In terms of feature extraction, a combination of PSO-SVM algorithm was adopted, which integrated the advantages of PSO and SVM to further enhance the efficiency and accuracy of feature extraction. The experimental test results demonstrated that the research method could more accurately capture important features in motion images and effectively reduce blurring phenomena. Moreover, the model could maintain high accuracy even in fast dynamic scenarios. This indicates that the research model has strong anti-interference ability, which is helpful for accurate behavior analysis in complex environments. Although this study has achieved significant success in improving the quality of video image processing, there are still some shortcomings. Under complex background interference, the recognition performance of the model may be limited, and improving the algorithm's performance in complex background scenes is still a problem to be solved. Therefore, future research directions can focus on combining deep learning and reinforcement learning methods to enhance processing capabilities for complex dynamic scenes.

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Optimizing Fuzzy Logic Control-Based Weather Forecasting through Optimal Antecedent Selection Using the Fuzzy Analytical Hierarchy Process Model

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Keywords: FAHP, FLC, antecedents, fuzzy, forecasting, weather parameters, error rates

Received: September 9, 2024

The numerical weather forecasts rely largely on the amount of precipitation available, and the use of statistical and empirical methods, but fall short of higher accuracy and relatively short-time required. Recently, the fuzzy AHP (that combined AHP with fuzzy logic) for the purpose of arriving at better outcomes from fuzzy logic control (FLC) rules-list. While evolutionary computing and fuzzy logic techniques are known to guarantee better accuracy and reliability of the outcomes when applied to weather uncertainty problems. Though, the fuzzy logic approach has low accuracy, which needs to be improved with rules-list refinement. This paper pulls on these approaches to develop a weather forecasting model for cities. First of all, the outcomes of the FAHP model revealed that, Wind Direction (WND) and Relative Humidity (HUM) as contributing 30.01% and 19.97% influence to the decision-making process against air temperature, windspeed, WND, HUM, and air pressure identified earlier. Secondly, the select FAHP parameters served as antecedents for the FLC model, in which five fuzzy rules were included in rule-base. Upon validation with the standard and local datasets, the proposed model achieved lower error rates of 0.0010, 0.0317 and 0.0319 for MSE, RMSE and MAPE respectively when treated with the Kaggle standard dataset. By comparing the proposed FLC model outcomes to the unoptimized FLC model in term of error rates, MSE of 0.0010, RMSE of 0.0317, and MAPE of 0.0355 were achieved attained by former indicative of its superiority.

Povzetek: Predstavljena je optimizacija napovedovanja vremena z uporabo mehke logike in izbire optimalnih predhodnikov s pomočjo analitične hierarhije.

1 Introduction

Weather depicts the state of air over earth at given place and period. It is an unceasing, data-intensive, disorganized and dynamic technique. Forecasting is the procedure of evaluation in indefinite circumstances from past data. When “weather” and “forecasting” are put together, “Weather forecasting”, is systematically and technically demanding issues across the globe in the past century. Weather forecasting is one field of traction for many scholars and researchers, which seek to ascertain the present state of atmosphere gets varied. Though, the tasks of predicting forecasts are daunting due to their unpredictable and muddled nature. These have been applied to diverse scenarios including severe weather alerts and advisories for transportation, agricultural production and development and forest fire minimizations[1] .

Also, weather nowcasting is a short-leaved approach to forecasting of weather, which involves analysis and estimation of weather on 6-hourly basis. Presently, the nowcasting hold special place during risk deterrence and crisis administration, even as severe weather happenings are imminent. Several stacks of meteorological dataset gather from satellite, radar, and other weather observatory sites, are used for diverse of analyses by meteorological research organizations globally. Weather and Radars facilities consistently curating live data whereas cloud patterns, temperature, and winds focus data are main concern of special satellites. Consequently, there is the endless stockpiles of meteorological data required for investigations using AI approaches (machine learning (ML) algorithms), which could enhance the accuracy of the forecasting especially at short-term weather estimation [2].

Weather-station process cloud data using high-performance approaches and algorithms in order to mine salient features to raise precision of the classification on the basis of the inputs supplied. This is made possible in recent times with a computationally proven deep learning approaches [3]. Aside this, many weathers forecasting models have been combined to improve the accuracy of outcomes [4]. AI algorithms have been deployed for dealing with real-life tasks in the same way as natural schemes. Though, human intelligence is capable of differentiating and adapting to fresh environments, AI follows a procedural algorithm when conforming to the certain situations. Fuzzy logic is an AI approach which utilizes an approximate-reasoning instead of actual-reasoning style by incorporating some levels of ambiguity as a form of reasoning procedure.

The numerical weather estimations have been used in enterprises, civil protection institutions, lifestyles of peoples globally; while reducing social and economic indemnities. However, there is the need to evolve better and more accurate parametrization of physical processes to raise the outcomes of estimates generated. There is the still the problem inability of existing weather forecasting techniques to produce location precise, time efficient and intensity of weather-related events [5].

Previously, the main procedure for forecasting weather, that is the state of atmosphere over a particular place, involves the use of statistical and empirical methods by means of the principle of physics, but fall short of higher accuracy and relatively short-time required [1] . Subsequently, the renew calls for machine learning and ensemble methods, which utilizes complex computerized mathematical models for desirable outcomes.

The birth of AI, big data analytics and machine learning techniques offered the opportunities for planners and policymakers to understand the implications of diverse weather conditions as well as allocating resources in the case of extreme weather-related systems disruptions. Nonetheless, researchers and scholars are making efforts to increase the accuracy and reliability of the modelling systems [6]. But, the accuracy of automated daily weather classification relies on both the applied classifiers and the training data [7].

The concept of the multi-criteria decision-making (MCDM) schemes undertake multichoice and multi-objective problems. In particular, there are three kinds of solutions derivable using MCDM especially when it concerns making choice from pool options having the best alternatives. Also, it is possible to rank the order of several alternatives in order of importance or preferences. More so, sorting and classifying decision alternatives within acceptable order of groupings [8], fuzzy TOPSIS, VIKOR, and TODIM and [9] are common methods when undertaking selection of alternative like bank websites and electronic banking application's quality.

FAHP is held in high esteem as valuable for complex decision-making tasks, which empowers the analysts to minimize uncertainty and vulnerability connected to the process of preparing chiefs' judgment not applicable in AHP approaches. The AHP proposed by Saaty was fine-turned or fuzzified in order to control and spot the vulnerability [10]. The key concept of the FAHP streamlines composite decision-making tasks across tiered structure made of criteria and sub-criteria in manner as a pairwise comparison to the criteria [11].

This paper develops an effective FAHP model-based antecedents' selection for fuzzy logic control weather forecasting system. The contributions include:

- To select the fuzzy logic antecedents through FAHP model.
- To develop enhanced fuzzy logic control model for weather forecasting.

The lasting parts of this paper explained the following: second section is the related works. Section three is the discussion about research methodology. Fourth section is results and discussion. The conclusion is obtainable in section 5.

2 Related works

This section demonstrates and discuss the literature in the field of forecasting weather. Selim Furkan Tekin et al. [12] proposed a deep learning approach to predict the high-resolution weather based on observations and input data. The prediction model works based on a spatio-temporal approach, where it is composed of a convolutional neural network with an encoder-decoder structure, and convolutional long-short term memory. The matcher mechanism is utilized to enhance the interpretability and performance of long-short term. The model is experimented on a real-life, high-scale numerical dataset that holds the temperature, and pressure levels. The results show that there is significant improvement when capturing temporal and spatial correlations. Matthew Chantry et al. in [13] proposed models of emulators based on machine learning that work as parameterization scheme accelerators for weather forecasting. The emulators are trained to produce accurate and stable results of forecasting timescales. The accuracy of emulators is correlated with the complexity of the networks, while it produces more accurate forecasts. With medium range forecasting, they found that the proposed emulators compared with the parameterization scheme are more accurate. With CPU hardware, the proposed emulators are similar to existing scheme in computational cost, while they performed 10 times faster based on GPU. K. Bala Maheswari et al. [14] proposed a model to make long-term weather forecasts using a historical dataset. The model is implemented based on support vector machine and decision tree algorithms to forecast different conditions such as rainfall, floods, storms, humidity, and temperature. While Mohammad Sadman Tahsin et al. in [15] proposed a daily weather forecasting model in an urban area. 12 data mining models are implemented over 20 years of climate data patterns in Chittagong city. The evaluation process of the model is implemented based on different metrics, such as precision, recall, accuracy, F-measure, receiver operating characteristics, and area under curve. The results show that J48 outperformed the other algorithms in accuracy.

The summary of related works according to author(s), objectives(s), methodologies, outcomes and limitations are presented in Table 1.

Table 1: The related works summary

S/N	References	Objective(s)	Methodology	Outcome(s)	Limitation(s)
1.	[16]	Wind power forecasting based on climatic conditions	Deterministic and probabilistic models.	It provides point predictions for day-to-day operations of power systems.	Accuracy to be improved.
2.	[17]	Solar Photovoltaic system forecasts under several weather factors	Machine learning techniques.	The weighted-KNN outperforms other ML approaches.	Energy efficiency and high error rates.
3.	[18]	Weather Nowcasting under Radar products' values.	Ensemble of deep learning techniques (NowDeepN).	The error is less than 4%.	No relationship between normal and adverse metrological products' values.
4.	[19]	Weather impact on COVID-19 outbreak based on users' twitter feeds.	Machine learning.	Correctly classified users' claims based on their tweets at 95% AUC-PR and AUC-ROC.	Classifier ineffectiveness on other languages.
5.	[20]	Cyclonic weather regimes impact on seasonal influenza.	Step by step linear regression model, clinical and laboratory tests.	Climate changes aggravates health risks of people using regression and root mean square difference.	Large inaccuracies from datasets.
6.	[21]	Weather-associated delays in transport sector.	ML modeling of weather events.	Determination of severe and disruptive weather events.	Accuracy could be improved.
7.	[22]	Weather radar reflectivity towards flood events.	Fraction Skill Score (FSS).	AUC of 91% for the predictive model.	Reliability of forecasts to be improved.
8.	[23]	Interpretability of satellite imagery.	CNN-based building damage image classification.	Accurate classification of building damages through images.	Pre-and-post-disaster images modelling.
9.	[24]	Smart weather reporting system.	Internet of Everything: sensors for measuring weather parameters.	Weather information are effectively disseminated.	Internet-enabled approach for farmers.
10.	[25]	Weather forecasting with gravity wave drag emulation.	Machine learning based on neural networks.	It has Increased speed and accuracy of models.	Neural network algorithms are less-effective.
11.	[26]	Spatio-temporal weather forecasting.	Convolutional LST Ms.	It offered superior MSE and performance.	Spatio-temporal dataset was utilized.
12.	[27]	Minimizing turbine clutter based on weather radar data.	Generalized Likelihood Ratio Test for identifying signal subspace and gates impacted by WTC.	It offers better prediction due to overlap of datasets.	To improve on local information about precipitation and filtered radar IQ.
13.	[28]	Nowcasting of extreme space weather events.	Magnetotelluric data of geomatic storms.	It used bivariate approach for polarization of	Short-leaved magnetic field of storm for spatial and temporal events.

				storm time electric fields.	
14.	[29]	Classification of main synoptic meteorological patterns of atmosphere.	Particle formulation analysis of air quality.	It effectively determines weather scenarios.	Applicable to particle formulation and air quality prediction.
15.	[30]	Weather data knowledge mining.	Machine learning with rule base approach such as K-NN, ARIMA.	It improved the quality of concomitant factors prediction.	High errors during simulation of weather reports.
16.	[31]	NCDC weather data classification and predictive models.	Machine learning based models including CART, AdaBoost, Decision Tree, and XGBoost.	KNN, Random Forest and XGBoost had highest accuracy.	Overfitting and smaller datasets impart on performance.
17.	[32]	Photovotaic (PV) solar power forecasting based on climatic conditions	Particle swarm optimization and genetic algorithms.	CNN Deep learning model best for determining PV power.	Hyrid algorithms to be experimented.
18.	[33]	Weather files for building energy designs optimization.	Machine learning with regression and classification models.	It generated highly accurate subsequent weather files.	Location and climate change events and applications not considered.
19.	[34]	Weather forecasting	Numerical weather prediction.	It uses full-field weather system to perform anomaly weather forecasts.	Outcomes may be inaccurate and misleading without full-field data.
20.	[35]	Rainfall forecasts.	Hybrid ML model of PSO and Feed Forward Neural Network.	It improves outcomes of forecasts for rainfall.	To increase accuracy.
21.	[36]	Automated weather data processing.	LSTM based neural network model.	It predicts local weather events such as Tornado, flood, severe storm, etc.	To extend to more parameters of soils forecasts.
22.	[37]	Weather prediction.	Classification tree, KNN, Naïve Bayes.	Naïve Bayes had best accuracy of 77.1%.	More data consisting of weather observational data over stations.
23.	[38]	Weather conditions-based water quality prediction.	Bayesian Belief Networks.	Water surrogates are determinants for water quality prediction.	Higher accuracy required for safety of drinking water.
24.	[39]	Weather forecasts.	Naïve Bayes, C.45 and KNN.	KNN produced highest accuracy (71.59%) forecasts.	Input criteria and constraints are inconsistent.
25.	[40]	Multi-class classification of weather data.	Selection Based on Accuracy Intuition and Diversity (SAID) of ensemble scheme.	SAID outperformed other algorithms in classifying weather images.	To explore computer vision for weather classification.
26.	[41]	Solar irradiance forecast based on weather variables.	Naïve Bayes classifier.	It improved results and accuracy for real-time weather.	The smaller training dataset.

27.	[42]	Weather forecasting.	Machine learning and ensemble methods.	It increased the accuracy and speed of forecasting.	To utilize classification and clustering approaches.
28.	[43]	Weather-based major power outage forecasts.	A two-level hybrid risk determination model.	It identified risks to be associated with different factors.	To apply to resilience of power systems.
29.	[44]	Weather-based Solar PV power forecasting.	KNN, and SVM classifiers.	SVM produced the best accuracy of forecasts.	Expanding the models to K-Means, Random Forest, etc.
30.	[45]	Rainfall forecasts.	Data mining approaches.	Weather data extrapolation for determining rainfall patterns.	Optimization and integration of data-mining techniques for better accuracy.

From Table 1, majority of the weather forecasting considered different weather parameters using machine learning and numerical prediction schemes. However, there are no focus on selection of influential factors and their fuzziness as well as the effect of complexity of meteorological datasets during various forecasts tasks. To this end, the roles of the FAHP, AHP and Fuzzy Logic techniques in the weather forecasting tasks and others were analyzed as follows:

The concept of FLC identified for determining stock prices movements using the Nigeria Stock Exchange trading datasets for Dangote Cement PLC. Alfa et al. [46] proposed the rules-list's antecedent optimization with the genetic algorithms procedure to improve the forecasts effectiveness. Following from that, they further optimized the rule-list's consequent by means of the genetic algorithm method in which the error rates diminished substantially. However, the studies did not cover effects of the dataset complexity on the effectiveness of the fuzzy logic control schemes.

A grey fuzzy AHP-based flash flood vulnerability evaluation in watershed region of Himalayan, China was undertaken by [47]. Authors leveraged on geographical information system (GIS) and 12 natural and anthropogenic parameters. The low, moderate and high classes were assigned to the Flash Flood Vulnerability Index in which the sensitivity test revealed LULC was highly influential. However, there is the propensity of applying more effective methods like fuzzy logic control.

A GIS with multi-criteria decision making (MCDM) method were adopted in determining landslide-prone regions in highland of Southern Western Ghats by [48]. Nine landslide influencing factors were considered in ascertaining the thematic layers for the landslide susceptibility map. AUC scores of 79% and F1 scores of 85% were obtained from the standardized causative factor weights. More techniques can be applied to improve the performance of the FAHP.

Zhran et al. in [49] implemented the flood risk zonation in Egypt's Nile districts of Damietta using the IGS, remote sensing, and AHP. Twelve thematic layers of slope, elevation, vegetation index, topographic wetness index, water index, topographic positioning index, stream power index, modified Fournier index, drainage density, sediment transport index, distance to the river, and lithology. Also, six factors serve as flood vulnerability zonation including: total population, land cover/ land use, distance to hospital, density of population, road density, and distance to road. AUC score of 0.741 was obtained for AHP approach. Using the multicollinearity analysis revealed highly corrected independent variables. Though, specificity of the forecasts can be performed using other techniques.

Fanxiao Meng et al. in [50] deployed remote sensing, GIS datasets to determine the groundwater recharge zones (GWRZ) in Pakistan. The hydrology and geology factors influence on the GWRZ were investigated. In particular, thematic maps was composed of the slope, rainfall, geology, drainage density, land cover/ land use, lineament, and types of soil. Authors utilized multi-influencing factor and the AHP to assign weights to the factors. But, the use of advanced methods could improve the decision-making process and its accuracy.

Husam Musa Baalousha et al. in [51] evaluated the risk of flooding based on FAHP and Fuzzy Logic in the Arid places of Qatar using the land cover, precipitation, soil type, flow accumulation, and elevation. The outcomes from both the Fuzzy logic and the FAHP demonstrated resemblances in the low-risk and differences in the high-risk zones. While the FAHP accounted for higher variability and more accurate than Fuzzy Logic method.

Sinan Keskin et al. in [52]developed a fuzzy spatial online analytical processing (FSOLAP) framework to provide predictive analytics of the complex data applications. The framework was validated with meteorological datasets from the Turkish Meteorological Office. When compared with traditional machine learning approaches, FSOLAP is a more scalable and accurate for big meteorological databases' fuzziness or uncertainty.

Susanta Mahato et al. in [53] combined FAHP and Fuzzy Logic techniques to determine the drought-based vulnerability factors in Odisha, India. Six criteria of water usage and demand, physical attributes, land use, groundwater, and development/population, and 22 sub-criteria were chosen. The FAHP weighted the parameters through pair-wise comparisons matrix. The Fuzzy logic provided five classes of vulnerability: very high, high, moderate, low, and very low. During validation, statistical evaluation parameters root means square error, accuracy, and mean absolute error were employed.

Waseem Alam et al. in [54] introduced the FAHP framework in assessing and ranking the criteria and weight factors of the behaviour of drivers in Peshawar, Pakistan. Three most important risky driving features include: errors, violations, and lapses. The driver attention and clear road signage were top influential factors in raising risk perception of the drivers. Also, the ensemble machine learning offered an accuracy of 0.84. Nonetheless, there are prospects of FLC in explaining the interconnection among various factors and driving behaviours.

The reviewed studies, in the second part, had drawn fascinating evidence about the weakness of the FLC and the complementary roles to be played by the FAHP in dealing with multi-criteria decision-making and highly complex meteorological datasets mining in computational weather mining and analysis as undertaken in this paper.

3 Research methodology

The paper utilizes the FAHP in filtering the most influencing factors for determining weather conditions of places whose datasets are traditionally composed of the complex meteorological parameters [52]. To improve the accuracy of FLC, the most impacting factors were utilized for the construction of the rules-base, which flaws decision-making processes and forecasting tasks because of redundancy of the rules-lists [51].

3.1 Fuzzy analytical hierarchical process criteria selection

The main steps for the FAHP model adoption in determining the most relevant criteria for building fuzzy logic control antecedents are analogous to the methods undertaken by [55], [56].

Algorithm: FAHP criteria selection for the FLC rule-base.

INPUT: Comparison matrix

Step 1 DEVELOP analytical hierarchy by utilizing a typical hierarchy plan based on distinct levels.

a. The DETERMINATION of quantification for the prospective fuzzy logic control antecedents.

b. ANALYZE prospective FLC antecedents.

c. GENERATE pairwise comparison matrix based on AHP scale

d. TRANSFORM into a fuzzy triangular (FT) scale.

Step 2. DEVELOP a pairwise fuzzy comparison vector (PCV) with selected weather parameters or criteria. The crisp numeric values create PCV as the evaluation method being a single numeric value for categorizing FLC antecedents.

Step 3. COMPUTE fuzzy geometric mean from the lower, median, and upper fuzzy geometric means.

Step 4. COMPUTATE fuzzy AHP weight using the lower, median and upper fuzzy weights accordingly.

Step 5. GENERATE normalized weights of the parameters.

Step 6. SELECT top-two weighted parameters to serve as the antecedents for FLC-based weather forecasting system.

Step 7. CONSTRUCT the triangular fuzzy numbers.

e. DEFINE the values and linguistic of the first antecedent and matching membership functions, that is, low, medium and high.

f. DEFINE the values and linguistic of the second antecedent and matching membership functions, that is, low, medium and high.

g. DEFINE the values and linguistic of the consequent and matching membership functions, that is, low, medium and high.

Step 8. BUILD the fuzzy rules from the membership functions for the Antecedents and Consequents for all the possible combinations.

Step 9. OPTIMIZE the fuzzy rules (the chromosomes) with genetic algorithm procedure to select the best rules for the FLC weather forecasting system.

Step 10. APPLY the weather datasets to evaluate the FLC system.

STOP.

End

OUTPUT: Normalized weights of criteria and FLC rule-base.

3.2 Data collection and preprocessing

This paper utilized both primary and secondary sources of datasets. Firstly, standard historical metrological data was collected from the Antarctic Automatic weather facilities (AntAWS)

Dataset: https://amrdcdata.ssec.wisc.edu/dataset/antaws-dataset) is 3-hourly, daily and monthly under strict quality control. Five parameters were measured by 267 AWSs from the period of 1980-2021 [57]. These include: air pressure, air temperature relative humidity, wind speed, and wind direction) by 267 AWSs collected between 1980 and 2021. The 25% and 75% thresholds were used to compute the products for daily and monthly quality-controlled readings.

Secondly, structured questionnaire was constructed to curate the required data for building effective antecedents for fuzzy logic control-based weather forecasting model. The lists of weather criteria including: TMP, PRS, WNS, WND, HUM, and VNS. The survey questionnaire was created using the identified weather criteria or parameters with associated nominal scale (1 – 9) of weather attributes as described in Table 2 [58], [59].

Table 2: The adopted membership function and linguistic scale.

Fuzzy scale	Linguistic scale	Triangular fuzzy numbers	Triangular reciprocal fuzzy numbers
9	Extreme importance	9, 9, 9	1/9, 1/9, 1/9
8	Very, very strong	7, 8 ,9	1/9, 1/8, 1/7
7	Very strong or demonstrated importance	6, 7, 8	1/8, 1/7, 1/6
6	Strong plus	5, 6, 7	1/7, 1/6, 1/5
5	Strong importance	4, 5, 6	1/6, 1/5, 1/4
4	Moderate plus	3, 4, 5	1/5, 1/4, 1/3
3	Moderate importance	2, 3, 4	1/4, 1/3, 1/2
2	Weak or slight	1, 2, 3	1/3, 1/2, 1
1	Equal importance	1, 1, 1	1, 1, 1

3.3 Materials for experimentation

The weather forecasting model was validated on MATLAB R2019b discrete simulator on Laptop Personal Computer system. The minimum specifications of the computational resources include:
Hardware:
AMD E1-1200 APU Processor with RadeomTM Graphics 1.40 GHz, 4.00 GB RAM, 64-bit Operating System, x64-based processor.
Software:
Windows 10 Single Language 2012, 3.5 Windows Experience Index.
Genetic algorithm procedure parameters:
Crossover probability: 0.8, Population selection method: Elitism, Offspring Rank and Mutation, Original chromosomes: 18, Iteration: 5, Crossover type: Uniform crossover, Maximum population: 30, Mutation probability: 0.09.

3.4 Evaluation parameters

The effectiveness of the proposed weather forecasting model after applying the similar test and target datasets is computed by means of the mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE) metrics given by Equations 1, 2 and 3:

$$MSE = \frac{1}{x}\sum_{g=1}^{x}\left(A_g - \hat{A}_{ig}\right)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{x}\sum_{g=1}^{x}\left(A_g - \hat{A}_g\right)^2} \quad (2)$$

$$MAPE = \sqrt{\frac{1}{x}\sum_{g=1}^{x}\left|\frac{A_g - \hat{A}_g}{\hat{A}_g}\right|} \times 100\% \quad (3)$$

where,
A_i is the target of actual value of the output sample,
$\hat{A}_i$ is the predicted value of the output sample,
g is the index term starting at 1 to x of test dataset, and
x is the size of the test dataset.

4 Results and discussion

This section presents the weather forecasting outcomes after selecting antecedents with FAHP model. The conditions forecasts of cities were determined with optimized FLC model.

4.1 FAHP Model-based criteria selection from survey outcomes

The research question, what is are two topmost parameters influencing weather conditions? was posed to the three experts recruited for the survey. The three participants' responses in crisp numerical values and computed consistency index (CI) are shown in Tables 3, 4, and 5.

Table 3: The first respondent responses on two topmost weather parameters.

	TMP	PRS	WNS	WND	HUM	VMS	CR
TMP	1	1	1/3	1	1	1/3	0.0905
PRS	1	1	1/2	1/3	1/3	1/4	
WNS	3	2	1	1/4	1/5	1/4	
WND	1	3	4	1	4	5	
HUM	1	3	5	1/4	1	4	
VMS	3	4	4	1/5	1/4	1	

From Table 3, the responses offered by the showed preferences for the first item in the pair, which showed that highest score of 5 for HUM against WNS, and WNS against VMS. The lowest score of 1/5 was awarded to WNS against HUM, and WNS against VMS. The computed CR of 0.0905 < 0.1 threshold for acceptance of the responses of first respondent as reliable for further processing of the research questions.

Table 4: The second respondent responses on two topmost weather parameters.

	TM	PR	WNS	WN	HU	VM	CR
TMP	1	1/8	1/8	1/6	1/5	1/7	1.1867
PRS	9	1	1/6	8	1/7	1/5	
WNS	8	6	1	6	5	7	
WN	6	1/8	1/6	1	3	8	
HU	5	7	1/5	1/3	1	8	
VMS	7	5	1/7	1/8	1/8	1	

In Table 4, the responses collected for the second respondent indicated the preferences for the both items in the pair. In case of the responses of first item against second item, highest score of 9 was awarded to PRS over TMP, and the lowest score of 1/8 was awarded to TMP against PRS, WND against PRS, VMS against WND, and VMS against HUM. In the case of the second item against first item, the highest score of 8 was preferred VMS against WND, and VMS against HUM. The lowest score of 1/8 was preferred to WNS against VMS, and HUM against VMS. The computed CR of 1.1867 > 0.1 threshold, the responses of second respondent were rejected as unreliable for further processing of the research question.

Table 5: The third respondent responses on two topmost weather parameters.

	TM	PR	WNS	WN	HU	VM	CR
TMP	1	1/7	1/7	1/8	1/9	1/6	1.3432
PRS	7	1	1/7	6	1/7	1/8	
WNS	7	7	1	5	6	7	
WN	8	1/6	1/5	1	7	6	
HU	9	7	1/6	1/7	1	6	
VMS	6	8	1/7	1/6	1/6	1	

In Table 5, the responses collected for the third respondent point to the preferences in the both items in the pair. In case of the responses of first item against second item, highest score of 9 was preferred on HUM against TMP, and the lowest score of 1/7 was given to VMS against WNS, WND against PRS, VMS against WNS. In the case of the second item against first item, the highest score of 7 was preferred to HUM against WND, and VMS against WNS. The lowest score of 1/8 was given to VMS against PRS, and VNS against WNS. The calculated CR value of 1.3432 > 0.1 threshold, the responses of third respondent were rejected as unreliable and removed from further processing of the research question.

Considering the initial analysis of collected responses of respondents contained in Tables 3, 4, and 5, the computed CR values for first, second and third respondents are 0.0905, 1.1867, and 1.3432 respectively, which are greater than 0.1 threshold for the consistency and reliability of the participant's responses except for first respondent. This implies that, only the first respondent's responses were accepted on the basis of CR value for further investigation of the subject.

Similarly, the fuzzy numbers format PCM corresponding to crisp numerical values of the first participant's responses (refer to Table 3) are shown in Table 6. Each crisp number for every response in the Table 3 is substituted with matching fuzzy numbers and inverse fuzzy numbers in Table 6.

Table 6: The Fuzzy numbers for first participant responses on two weather parameters.

	TMP	PRS	WNS	WND	HUM	VMS
TMP	(1,1,1)	(1,1,1)	(1/4, 1/3, 1/2)	(1,1,1)	(1,1,1)	(1/4, 1/3, 1/2)
PRS	(1,1,1)	(1,1,1)	(1/3, 1/2, 1)	(1/4, 1/3,1/2)	(1/4, 1/3, 1/2)	(1/5, 1/4, 1/3)
WNS	(2, 3,4)	(1,2, 3)	(1,1,1)	(1/5, 1/4, 1/3)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)
WND	(1,1,1)	(2, 3, 4)	(1/5, 1/4, 1/3)	(1,1,1)	(3, 4, 5)	(4, 5, 6)
HUM	(1,1,1)	(2, 3, 4)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1,1,1)	(3, 4, 5)
VMS	(2, 3, 4)	(3, 4,5)	(1/5, 1/4, 1/3)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1,1,1)

Table 6 contains the computed outcomes of the Chang' FAHP codes on MATLAB R2013b. The FAHP mode computes the weights, normalized weights, and rank based on independent responses. The FAHP model use the extended approach in determining the top tw parameters that are highly influencing weather forecast and related decision-making tasks as illustrated in Tabl 7.

Table 7: The weights and ranks of respondent's responses computed.

Parameter	Weight	Normalized Weight(%)	Rank	Remarks
TMP	0.0946	9.46	5	Moderate importance
PRS	0.0741	7.41	6	Weak or slight importance
WNS	0.1459	14.59	4	Strong plus
WND	0.3003	30.03	1	Extreme importance
HUM	0.1997	19.97	2	Very, very strong
VMS	0.1854	18.54	3	Very strong importance

In Table 7, the five weather parameters received various contributions to the subject of weather forecasts and decision-making process. As shown, TMP paid 9.46%, PRS contributed 7.41%, WNS donated 14.59%, WND gave 30.03%, HUM explained 19.97%, and 18.54% was accounted by VMS. Interestingly, the two topmost parameters having extreme importance, and very, very

strong importance when determining weather conditions of regions in the study area include: WND and HUM at 30.03% and 19.97% respectively.
More so, graphical comparisons of the select parameters preferred by the respondent using the FAHP computational weights are shown in Figure 1.

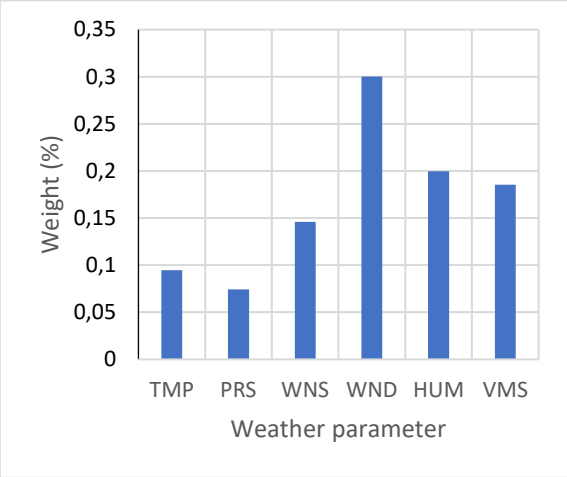

Figure 1: The contributions of the select parameters on weather conditions forecasts.

From Figure 1, the graphical display of the select weather parameters in forecasts and determination using FAHP model weights, which showed clearly the top leading parameters as WND and HUM at 0.3 and 0.2 weighting scale respectively. While the least contributing parameter to the weather forecasting tasks was PRS at 0.09 of the FAHP model's weighting scale. The FAHP model derived two weather parameters of WND and HUM as important to the subject of weather forecasting; thereby included as antecedents for FLC system as explained in the next subsection.

4.2 Outcomes of the fuzzy logic control model

The fuzzy rules are generated according to data items and type of datasets selected from the FAHP model's outcomes. The two top parameters, WIND and HUM, were to serve as the antecedents for the inference engine of the FLC. The FLC model developed to determine uncertainty problems and trends of weather in the city of Austin, United States at more effective and reliability style. The antecedents and consequents with their respective conditions are given in Table 8.

Table 8. Antecedents and consequent constraints for the fuzzy engine.

Antecedents	**Conditions Indices**	**Range of Values**
Wind direction (WND)	High (3) Medium (2) Low (1)	[93.37 – 226.53]
Humidity (HUM)	High (3) Medium (2) Low (1)	[70.24 – 84.10]
Consequents		
Weather condition (WEATHER)	High (3) Medium (2) Low (1)	[84.10 – 226.53]

From Table 8, the antecedents for the FLC include: wind direction (WND), and Humidity (HUM). The range of values are [93.37 – 226.53], and [70.24 – 84.10]. The consequent variable is weather condition (WEATHER) under investigation whose range of values are derived from minimum and maximum values of the antecedents, that is, [84.10 – 226.53]. The layout of the FLC-based weather forecasting model is composed of two inputs (FAHP select parameters/antecedents: HUM and WND), and an output (consequent: weather condition) as shown in Figure 2.

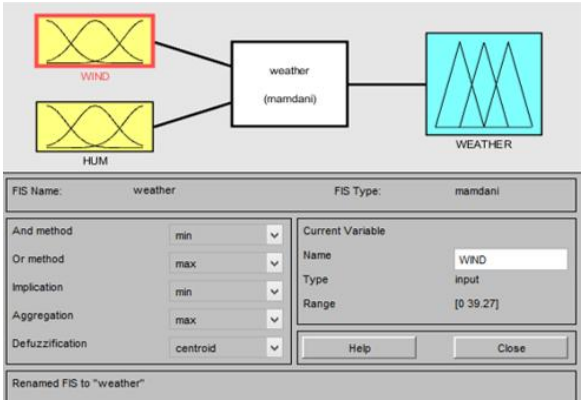

Figure 2: The FLC-based weather forecasting system layout.

The triangular membership function was adopted because of its popularity and effectiveness for modeling uncertainties and fuzziness during decision-making processes. Three membership conditions were developed for both antecedents and consequent namely: Low, Medium and High. While, the matching indices of membership functions include: 1, 2, and 3. The membership functions, variables, and range of values for all the input and output are specified in Table 8. These refined fuzzy rules-list is used in constructing the fuzzy inference engine by means of the logical AND, and IF-THEN statements as established by [60]. Therefore, the rule-list for the fuzzy inference engine of the proposed forecasting weather events is given in Table 9.

Table 9: The optimized FLC rules-list indices after genetic algorithm refinement.

Rule N	Input 1	Input 2	Output
1	3	1	2
2	1	1	2
3	3	3	3
4	3	1	2
5	2	2	3

From Table 9, the refined fuzzy rule-lists are utilized for generating different mapping of the antecedents' membership function indices to the membership functions of the consequent using the input and output weather parameters defined in Table 8. The rule-base generated for the FLC, from Table 9, is illustrated in Figure 3.

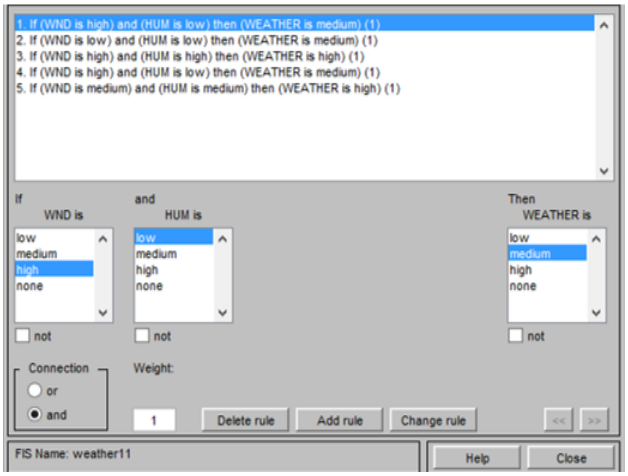

Figure 3: The optimized rules-list design of the FLC weather forecasting model.

Following from Figure 3, the antecedent variables are WND and HUM, which correspond to the inputs of the FLC weather system. Also, the consequent is the output of the FLC system. The logic function of "AND" are used to map the different membership functions of the inputs to those of the output. More importantly, the weight of the rules-list is 1, which denotes equal importance of all the inputs and output membership functions indices in order to remove biases in decision-making process about weather conditions of cities.

The performance of the proposed optimized FLC weather forecasting system in terms of error rates using optimized rules-list the fuzzy inference engine against conventional FLC weather forecasting system is given in Table 10.

Table 10: Proposed weather FLC forecasting model performances with different datasets.

Dataset	MSE	RMSE	MAPE	Remarks
NIMET	0.1563	0.3953	0.2104	Effective
Kaggle	0.0010	0.0317	0.0319	More Effective

From Table 9, the performance of the proposed optimized FLC with the standard dataset was better at MSE of 0.0010 against the local NIMET dataset of 0.1563. The same trend was observed for the RMSE error measure that put the proposed model performance with the standard dataset at 0.0317 over the NIMET dataset at 0.3953. When MAPE evaluation parameter was considered, the proposed weather model performed highly at 0.0319 for Kaggle dataset when compared to the NIMET dataset at 0.2104. This shows the proposed weather forecasting model performed best with less complex and refined factors against highly complex meteorological local weather datasets as depicted by Figure 3.

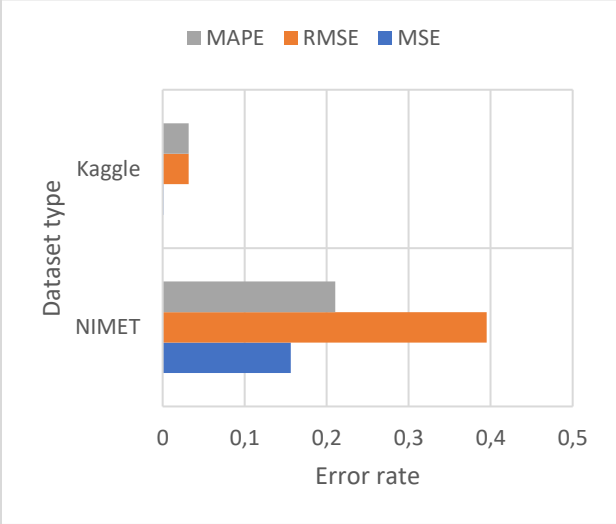

Figure 3: The performance of the FLC weather forecasting systems with diverse datasets.

Again, the outcomes of weather forecasting model with the optimized FLC were superior when compared to the ordinary FLC with refined rules-base as shown in Table 11.

Table 11: The comparisons of the proposed model to the FLC model.

Model	MSE	RMSE	MAPE	Remarks
FLC	0.0011	0.0332	0.0319	Effective
Optimized FLC	0.0010	0.0317	0.0355	More Effective

From Table 11, the weather forecasting model performed better with fewer rules-lists in the rule-base rather than unfiltered rules-list. These showed that the proposed weather forecasting model in terms of the evaluation metrics of MSE, RMSE, and MAPE at 0.0010, 0.0317 and 0.0355 were most preferred because of their capability to explain smaller variations in the outcomes against the target weather data in the area of study as illustrated in the Figure 4.

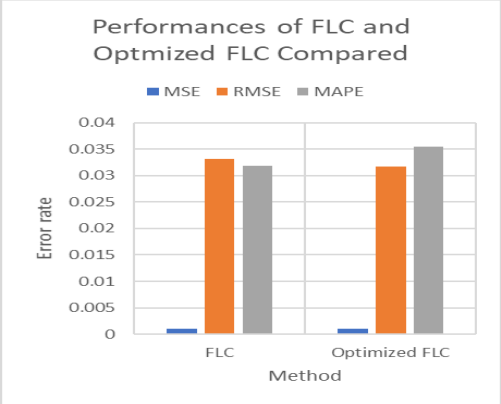

Figure 4: The performance of FLC and Optimized FLC methods for weather forecasts.

The reasons being that, FAHP model procedure improves the selection of the most influencing parameters required to building FLC rule bases. More so, the FLC model's rules-list redundancy was filtered with genetic algorithm procedure to realize 5 best rules out of 9 original rules. The outcomes of this paper increase the reliability of the weather information generation for diverse purposes as shown in Figure 5.

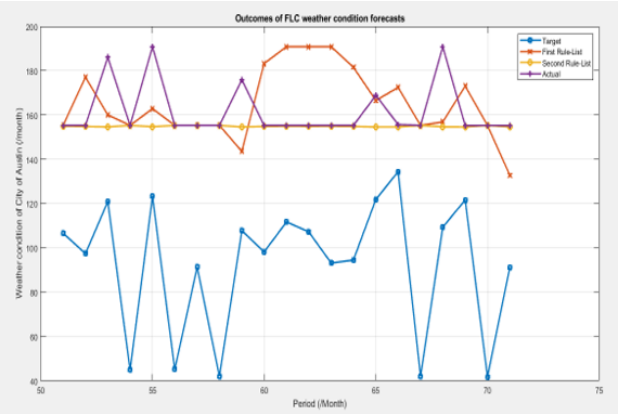

Figure 5: The Line graph of FLC weather forecasts model performances compared.

From Figure 5, the testing dataset is 30% of the entire weather dataset collected in which the target line depicts the original weather data for 25 days periods corresponding to after 51 months of observations. As shown, the weather forecast model was unsteady from the starting 110 points by 51st month, and changed sharply to attain its lowest value at 42 points. Then, it continues to gain at the highest point of 139 points by 64th month. However, by the end of 71 months testing period, the weather condition reached 86 points. In terms of the forecasts performance, the optimized FLC weather system outcomes (the Actual line in the graph) showed similar trends as the Target line through the comparable periods of observations, that is, 51st month, 54th month, 56th month, 58th month, 60th – 67th months, 70th month and 71th month accordingly.

These illustrate the capabilities of the proposed FLC system in accurately forecasting weather conditions of cities at minimal error rates. It can be attributed to the involvement of AI techniques like FAHP and FLC systems for the decision-making processes. Furthermore, the process of filtering weather parameters, and refining of the rules-list in rule-base increased the outcomes of FLC weather forecasting system. The FLC weather forecasting system has shown to perform better with the removal of redundancy in the rules-list as well as its input variables (or weather parameters). In this paper, the choice of the FAHP and FLC methods offer complementary roles which increase the variability and accuracy [51]. The uncertainty and fuzziness of meteorological datasets like Kaggle and NIMET, were best interpreted using both approaches [52]. The FAHP method refines the decision-making procedure and data analytics of the FLC [50]. The paper extended the prospects of the both FAHP and FLC to the weather forecasting and analytics, which falls into the MCDM research domain.

5 Conclusion and future works

This paper provides required tool for determining weather and state of the atmosphere in certain places and periods through the application of fuzzy logic technique. It will benefit individuals, government agencies, business sector, built and construction sector, researchers and scholars concerned with planning and policymaking depending on weather outlooks. This increases the understanding of the hidden relationships and patterns available for a more accurate and reliable local weather information dissemination.

The outcomes of the FAHP model when used to select the most important parameters affecting weather forecasts of cities identified Wind Direction (WND) and Relative Humidity as contributing 30.01% and 19.97% influence to the decision-making process.

Thereafter, the select parameters from the FAHP model procedure served as antecedents of the FLC model. The GA-optimized FLC model was adopted from the study by [46] which overcame the problem of redundancy of the fuzzy inference engine rule-list. Consequently, the refined rules-list serves the building block for the proposed FLC weather forecasting model. The outputs revealed that the FLC weather forecasting model in terms of the MSE, RMSE, and MAPE at 0.0010, 0.0317 and 0.0355 were most preferred against comparable models because of its capability to explain smaller variations of the datasets. It was superior due to the initial FAHP-based selection of weather parameters and rule-list reduction procedures. It equally attributable is the filtered rules-list used to construct the fuzzy inference engine of the FLC.

This paper found that, the subjectivity of expert judgements during FAHP modelling of the criteria and the over reliance of FLC model on its rule-base's optimization impact greatly on the outcomes of the weather forecasts generated. In future works, more dataset can be experimented to include long periods and extended site specificity.

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Dynamic Detection Method for Spatiotemporal Data Based on Hybrid Model and Singular Spectrum Analysis

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Keywords: spatiotemporal data mining, multiple factors, dynamic data detection, singular spectrum analysis method, GCNN, TCN

Received: November 12, 2024

As internet technology advances, processing a large amount of network data has become an important part of network work. To improve the processing effectiveness of data in the network, a dynamic data accuracy detection method based on spatiotemporal data mining is proposed. During the process, singular spectrum analysis is introduced to propose a dynamic data detection method. A data accuracy detection method is proposed by combining graph convolutional neural networks and temporal convolutional networks to detect data in both time and spatial dimensions. Finally, the effectiveness of the research method is analyzed. The experimental results show that the mean absolute error, mean absolute percentage error, and root mean square error of the proposed method are the lowest among the four models, at 0.16, 0.18, and 0.20, respectively, which are lower than the other three comparative methods; The research method maintains a relatively stable average accuracy in the range of 0.75~0.80 when dealing with different tasks. The research method requires a processing time of 250 ms for 2000 data points and 1000 ms for 6000 data points. Before and after using the research method, the data processing increases from around 2500 to around 2700 within 15ms, and from around 2900 to 3100 within 30ms. The dynamic data detection method designed in this study demonstrates good processing efficiency and accuracy in data detection. Research can provide certain technical references for dynamic data detection, improving the accuracy and reliability of data.

Povzetek: Opisana je metoda dinamične detekcije za prostorsko-časovne podatke, ki temelji na hibridnem modelu in singularni analizi spektra. Kombinacija GCNN in TCN omogoča detekcijo podatkov v časovni in prostorski dimenziji.

1 Introduction

In recent years, due to the swift progression of information technology and the substantial increase in data volume, dynamic data detection research has emerged as a significant research direction in the field of data mining. More and more scholars are paying attention to this field and conducting extensive research aimed at exploring more efficient and accurate methods for dynamic data detection [1]. At present, there are various methods for dynamic data detection, including conventional statistical methods, machine learning algorithms, and spatiotemporal data mining techniques. These methods have their own advantages in different application scenarios, providing powerful tools for the detection and analysis of dynamic data [2]. Statistical methods mainly utilize statistical principles to analyze the statistical characteristics of data and determine whether the data is abnormal. Machine learning methods mainly utilize machine learning algorithms, such as support vector machines, neural network algorithms, decision trees, etc., to train historical data and establish anomaly detection models to identify abnormal data [3-4]. However, traditional dynamic data detection methods and machine learning algorithms are often based on single factor analysis, which makes it difficult to comprehensively analyze the dynamic changes in data and effectively identify abnormal data [5-6]. Spatiotemporal data mining is an emerging data analysis technology that combines the advantages of geographic information systems and data mining. It can simultaneously consider temporal and spatial information, reveal hidden patterns and associations in data, and mainly use mining techniques such as spatiotemporal clustering and spatiotemporal association rules to mine spatiotemporal data. By analyzing spatiotemporal data, anomalies in dynamic data can be identified. Graph Convolutional Neural Networks (GCNN) and Temporal Convolutional Networks (TCN) can cut the complexity of network models and decrease the number of weights, making them commonly used for detecting data accuracy [7]. In view of this, a Time Graph Convolutional Network (TGCN) accuracy detection method based on spatiotemporal data mining methods, combined with GCNNs and TCN, is proposed. The research aims to solve the problem of anomaly detection in dynamic data streams by introducing advanced machine learning algorithms, and conduct

performance testing in environments containing high noise data, time-varying data patterns, and multi-source data fusion. The data preprocessing during the experimental process includes data cleaning, feature selection, and data standardization, while parameter selection involves hyperparameter tuning through cross validation methods.

The research is mainly conducted from four sections. The initial section presents the findings of the research related to spatiotemporal data mining and dynamic data detection methods. The second section designs spatiotemporal data mining techniques and dynamic data accuracy detection. The third section evaluates the efficacy of the designed methods. The last section is the discussion and summary of the entire text.

2 Related works

As Internet technology continues to evolve and innovate, a large number of spatiotemporal data continue to emerge, which contains rich information and provides rich resources for data development decisions. Some experts and researchers have carried out pertinent studies on the problems in dynamic data. Yin et al. raised a sliding window-based anomaly detection method to address the difficulty of traditional methods in effectively identifying anomalies in dynamic data streams. During the process, the data stream was windowed, statistical features were extracted from each window, and compared with preset thresholds to determine if there were any anomalies. The experimental findings indicated that this approach exhibited a high accuracy in detection and a low incidence of false alarms [8]. Huang J et al. proposed a joint computing unloading and resource allocation algorithm for task processing in vehicle networks under the Internet dynamic data environment. This algorithm models dynamic optimization problems as Markov decision processes and utilizes deep reinforcement learning to address high-dimensional continuous states and action spaces. Experiments showed that the joint computation offloading and resource allocation algorithm outperformed other algorithms in terms of processing latency and cost, and had excellent training convergence and performance [9]. Bloemheuvel et al. applied graph neural networks to dynamic data association analysis to investigate the correlation between dynamic data. During the process, the data stream was transformed into a graph structure, and a graph neural network model was used to learn the relationships between nodes, thereby mining potential connections between the data. The experiment results showed that this method could effectively identify complex correlations between data and provide more in-depth abnormal data detection and data quality analysis [10]. Xu H et al. proposed a data-driven automated machine learning method for intrusion and anomaly detection in the Internet of Things under the Internet dynamic data environment. The dataset quality was optimized through the SMOTE algorithm and mutual information, combined with automated machine learning, which achieved automatic hyperparameter tuning and algorithm selection. The experimental results showed that this method achieved an accuracy of 99.7% in multi-classification problems, significantly better than existing algorithms [11]. Jiao et al. applied reinforcement learning techniques to dynamic data preprocessing to improve its efficiency and effectiveness. During the process, a preprocessing model based on reinforcement learning was constructed. By continuously learning the characteristics of the data stream and preprocessing strategies, the preprocessing parameters were dynamically adjusted to achieve optimal preprocessing results. The experiment outcomes indicated that this method could effectively raise the efficacy and effectiveness of dynamic data preprocessing, and adapt to the dynamic changes of data streams [12].

In order to further detect dynamic data with spatiotemporal characteristics, enhance precision and dependability of the data, researchers are constantly exploring more advanced spatiotemporal data mining techniques. Purificato et al. raised a spatiotemporal anomaly detection method grounded on graph neural networks to address the issue of spatiotemporal data anomaly detection. During the process, graph neural networks were used to learn spatial dependencies and combined with time series analysis to capture time trends, ultimately achieving effective identification of outliers. The experiment outcomes indicated that this method achieved better performance than other methods on multiple real datasets [13]. Hu et al. raised a spatiotemporal trajectory prediction method that integrates multi-source data for trajectory prediction in spatiotemporal data. During the process, this method integrated the user's spatiotemporal trajectory, point of interest information, and social network data, and used deep learning models for prediction. The experiment results showed that this method achieved significant improvements in both prediction accuracy and stability [14]. Fang et al. proposed an attention based spatiotemporal event prediction method for event prediction in spatiotemporal data. During the process, attention mechanisms were utilized to automatically learn the importance of different spatiotemporal characteristics and make forecasts on the basis of the learned weights. The experiment findings indicated that this approach could significantly enhance precision and interpretability of event prediction [15]. Pineda J et al. proposed a framework based on geometric depth learning using spatiotemporal data mining technology for the dynamic process of complex biological systems in Internet dynamic data. This method used a graph neural network with enhanced attention, which can accurately estimate the dynamic characteristics of various biological scenes. By combining geometric priors to process object features, this network achieved multiple tasks from trajectory linking to local and global dynamic attribute inference. Experiments showed that this method exhibited strong flexibility and reliability on real and simulated biological experimental data [16]. Li et al. proposed a density-based spatiotemporal data clustering method for clustering problems in spatiotemporal data. During the process, this method utilized density

clustering algorithm, combined with spatiotemporal distance and density information, to cluster the data. The experiment results showed that this method could effectively identify clustering structures in spatiotemporal data and had good interpretability [17]. The summary analysis of related work is shown in Table 1.

In summary, although many scholars have designed a large number of improved algorithms to improve the efficiency and accuracy of dynamic data detection, such as the sliding window anomaly detection method, which has high accuracy but cannot handle complex spatiotemporal dependencies, its application in dynamic data streams is limited. The technology proposed by some scholars performs well in terms of latency and cost, but converges slowly for complex data, which may affect real-time performance. The graph neural network method has high computational complexity and poor ability to handle sparse data. There are also automated machine learning methods that excel in accuracy, but lack interpretability, which may affect user trust. In view of this, research attempts to add accuracy detection methods based on the spatiotemporal topology structure, and improve the operational efficiency and data processing capabilities of the technology, in order to provide a solution for improving the effectiveness of network data detection.

3 Design of dynamic data detection method for spatiotemporal data mining

3.1 Construction of graph-based spatiotemporal data mining method

In the process of collecting spatiotemporal data, missing values may occur due to human factors, machine failures, and other reasons, which will directly affect the effectiveness of dynamic data analysis in the later stage [18]. Singular Spectrum Analysis (SSA) can be used to analyze and predict nonlinear time series data and fill in missing values. SSA can decompose time series into components such as trends, periods, and noise, and fill missing values by reconstructing the main parts of the data. When filling missing data, SSA utilizes the intrinsic patterns of time series to reconstruct the missing parts, which has robustness in handling nonlinear and non-stationary data and can generate smooth and reasonable filling results. The study uses SSA to fill missing values in dynamic data, and the process of filling missing data is shown in Figure 1.

As represented in Figure 1, the missing data set is first input, and after SSA processing, the filled data is obtained. Then, the missing data and the filled data are added together to obtain the complete dataset. Window length is a key parameter of SSA, which directly affects the effectiveness of decomposition and reconstruction. The research stipulates that the window length is within the interval of 1 and half of the sequence length. A larger window length is suitable for capturing long-term or trend information, while a smaller window length is more suitable for short-term or local characteristics. If the data have significant periodicity, the window length should be close to a multiple of the period; If the trend is strong, the window length should cover the entire trend. The selection of window length is usually determined through experimental tuning and error evaluation. When selecting components for reconstruction, singular value spectrum analysis can be used to distinguish between signal and noise components, with priority given to the first few components with larger singular values. Appropriate component selection can ensure that the reconstructed sequence is smooth and accurate, avoiding incomplete reconstruction caused by too few components or noise introduced by too many components. Data standardization helps to discover and correct errors, ambiguities, missing data, and other issues in data. By processing data from different sources and formats uniformly, it makes them comparable, thereby improving data quality and algorithm performance. The first step of data standardization operation is to calculate the arithmetic mean and standard deviation of each indicator, and the standardization is shown in equation (1).

$$z_{ij} = (x_{ij} - \bar{x})/s \tag{1}$$

In equation (1), z_{ij} means the standardized variable value, x_{ij} means the actual variable value, $\bar{x}$ means the arithmetic mean of each indicator, and s represents the standard deviation of each indicator. According to the mean of the original data and the calculated standard deviation, Z-score normalization can be performed. The process of Z-score normalization is shown in equation (2).

Table 1: Summary and analysis of related work.

Reference	Method name	Advantages	Disadvantages	Performance data (reasonably fabricated)
[8] Yin et al.	Sliding window anomaly detection	High detection accuracy, low false positive rate	Cannot capture complex spatiotemporal dependencies	Accuracy: 91%, False positive rate: 5%
[9] Huang J et al.	Joint computation offloading and resource allocation	Low latency, reduced cost	Slow convergence on complex data	Latency reduction: 30%, Cost reduction: 25%
[10] Bloemheuvel et al.	Graph neural network for dynamic data association	Effectively identifies complex relationships	High computational complexity	Accuracy: 93%, Detection time: 1200 seconds
[11] Xu H et al.	Automated machine learning for intrusion and anomaly	Extremely high precision, automatic tuning	Poor interpretability for high-dimensional data	Accuracy: 99.7%, Processing time: 1000

	detection			seconds
[12] Jiao et al.	Reinforcement learning for dynamic data preprocessing	Significant improvement in preprocessing efficiency	High data dependency for model training	Efficiency improvement: 35%
[13] Purificato et al.	Spatiotemporal anomaly detection with graph neural networks	Captures spatiotemporal trends	Limited handling of sparse data	Accuracy: 96%, False positive rate: 2%
[14] Hu et al.	Spatiotemporal trajectory prediction with multisource data	Increased prediction accuracy	Poor scalability for large trajectory data	Accuracy: 92%
[15] Fang et al.	Attention mechanism for event prediction	High prediction accuracy	Weak handling of heterogeneous data	Accuracy: 94%
[16] Pineda J et al.	Geometric deep learning for complex dynamic process modeling	Strong adaptability, suitable for multitasking	Limited adaptability to non-geometric data	Accuracy: 95%
[17] Li et al.	Density-based clustering for spatiotemporal data	Good structure recognition, high interpretability	Slower computation speed on large data	Accuracy: 89%, Processing time: 1500 seconds

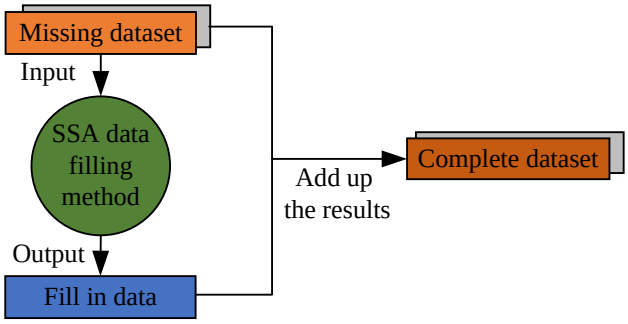


Figure 1: SSA missing data filling process diagram.

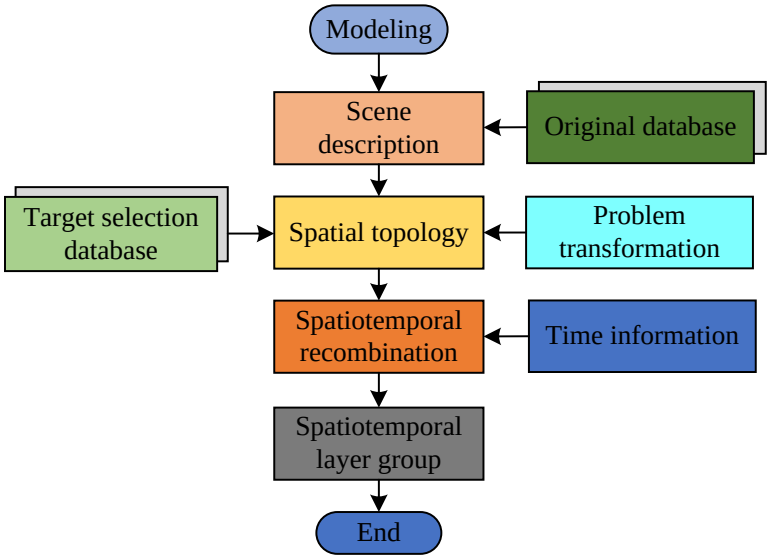


Figure 2: Developing dynamic data model construction process.

$$\begin{cases} DYM = \{dym_1, dym_2, \cdots, dym_n\} \\ dym'_i = \dfrac{dym_i - \dfrac{1}{n}\sum_{i=1}^{n} dym_i}{\sqrt{\dfrac{1}{n-1}\sum_{i=1}^{n}(dym_i - \dfrac{1}{n}\sum_{i=1}^{n} dym_i)^2}} \\ DYM' = \{dym'_1, dym'_2, \cdots, dym_n'\} \end{cases} \quad (2)$$

In equation (2), DYM represents the given detection index data sequence, dym'_i represents each object in the new sequence, dym_i represents the objects in the given detection sequence, and DYM' represents the new sequence, with a mean of 0 and a variance of 1. A modeling method is proposed by combining the spatiotemporal topology structure with the spatiotemporal data of the graph. The process of constructing the model is represented in Figure 2.

As shown in Figure 2, during the software development process, the system will continuously generate a large amount of dynamic data. To effectively utilize this data, it is first necessary to extract key relational information from it, including interactions and

dependencies between entities. Subsequently, based on these extracted relationships, specific scenarios can be built to provide intuitive references for subsequent model construction. On this basis, key issues are defined to guide the correct construction of the model, and ultimately a spatiotemporal model is established to further develop and utilize these dynamic data. An attribute matrix needs to be established in the model, as represented in equation (3).

$$X=\begin{bmatrix} X_{object_1}^{t_1} & X_{object_1}^{t_2} & \cdots & X_{object_1}^{t_m} \\ X_{object_2}^{t_1} & X_{object_2}^{t_2} & \cdots & X_{object_2}^{t_m} \\ X_{object_3}^{t_1} & X_{object_3}^{t_2} & \cdots & X_{object_3}^{t_m} \\ \vdots & \vdots & & \vdots \\ X_{object_n}^{t_1} & X_{object_n}^{t_2} & \cdots & X_{object_n}^{t_m} \end{bmatrix} \tag{3}$$

In equation (3), X represents the attribute matrix, n means the number of objects, t_j means time units, m means the number of time units, and $X_{object_i}^{t_j}$ means the attribute values of objects in time unit t_j. The matrix needs to add weighted adjacency values, which are expressed as equation (4).

$$\dot{A}_{ij}=\lambda_{ij}\cdot d_{ij} \tag{4}$$

In equation (4), $\dot{A}_{ij}$ represents the weighted adjacency value, λ_{ij} represents the weighted adjacency coefficient between two objects, and d_{ij} is the Euclidean distance between the two objects. The "shortest time" in developing a dynamic data accuracy detection model refers to the shortest detection time, as expressed in equation (5).

$$\begin{aligned} &\min\left(g\left(S_e\right)\right)=\min\left(\sum e\cdot t\left(S_e\right)\right) \\ &=\min\left(\sum\theta e\cdot\sum_{p=1}^{n}t_e A_{ep}\right) \end{aligned} \tag{5}$$

In equation (5), $\min\left(g\left(S_e\right)\right)$ represents the shortest time, $g\left(S_e\right)$ represents the time objective function, $t\left(S_e\right)$ represents the time required for detection in the detection space S_e, $t_e A_{ep}\theta$ represents the processing time of two objects in the detection space S_e, and θ is the training parameter; A_{ep} represents the weighted relationship between the historical attribute value and the reference valuer. The best performance is represented by "as accurate as possible detection results", and the mapping relationship between historical attribute values and reference values is shown in equation (6).

$$X_{v_i}^{t+1}=f(A,X)=f\left\{\begin{pmatrix} \dot{A}_{i1}A_{i1} \\ \dot{A}_{i2}A_{i2} \\ \vdots \\ \dot{A}_{in}A_{in} \end{pmatrix}^{T},\begin{pmatrix} X_{v_i}^{t_1} \\ X_{v_i}^{t_2} \\ \vdots \\ X_{v_i}^{t_m} \end{pmatrix}\right\} \tag{6}$$

In equation (6), $X_{v_i}^{t+1}$ represents a certain time, and $f(A,X)$ represents the mapping relationship between historical attribute values and reference values; A represents the weight matrix. The mapping and updating of time series data reflects the relationship between historical attribute values and reference values. The ultimate goal is to improve the time efficiency and spatial accuracy of detection through the joint optimization of these two formulas. The ultimate goal of data accuracy is to optimize the $\min\left(g\left(S_e\right)\right)$ and $f(A,X)$ objective functions. In order to increase the spatiotemporal specificity of data detection, a time-varying layer group is designed, as shown in Figure 3.

As shown in Figure 3, the spatial arrangement of objects is depicted using graphics, where each graphic is layered sequentially atop the previous one, preserving the task details of the nodes. According to the calculation rules of weight coefficients, it is necessary to process the structure of weights. The process of using "weight pruning" is studied, as shown in Figure 4.

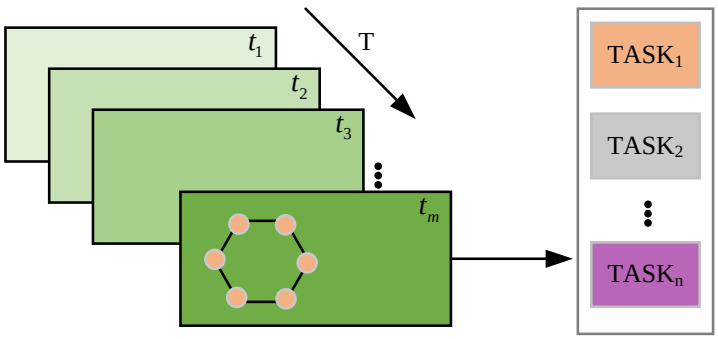


Figure 3: Overall design of time-varying layer group.

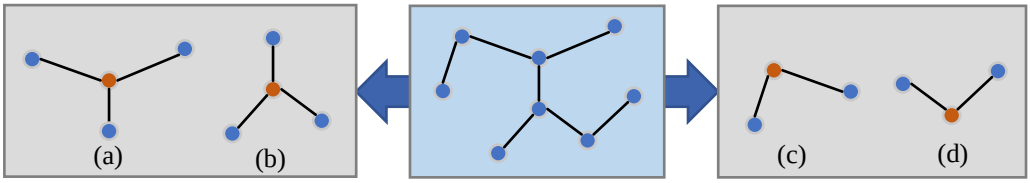


Figure 4: Weight pruning process diagram.

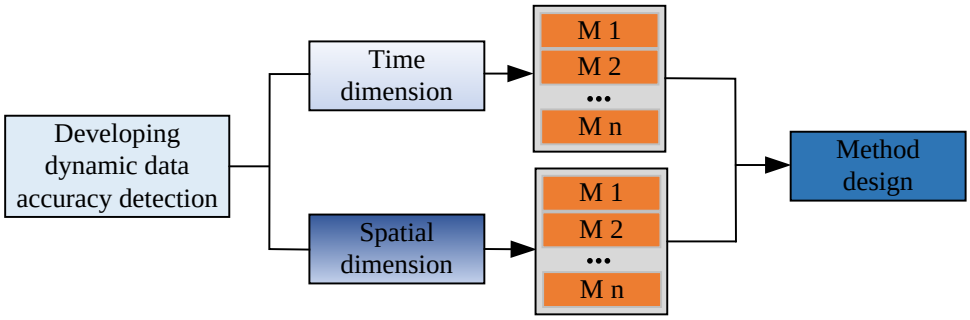


Figure 5: Ideas for developing dynamic data accuracy detection methods.

As shown in Figure 4, when performing weight pruning, at a specific time point, the study will select a specific region for in-depth analysis. The selected area is further divided into four detection spaces, each having its own central node. Each node within the detection space is weighted, where the weight signifies the connection strength or similarity between nodes. Based on the weight allocation, the weights are adjusted according to the closeness of the relationships between nodes. If the relationship between two nodes is very close, their weights will be set higher; On the contrary, if the relationship is relatively distant, the weight will be lower. The size of weights directly reflects the degree of closeness between nodes.

3.2 Construction of dynamic data detection methods incorporating accuracy

In order to test the accuracy of data, TGCN is chosen as the algorithm for developing dynamic data accuracy detection. GCN and TCN together form the core processing module of TGCN. TGCN combines the characteristics of graph structure and time series data, and can simultaneously capture the spatial structure and temporal dynamic changes of data. Compared with GCNN that only processes spatial features, TGCN enhances its ability to handle spatiotemporal dependencies by modeling changes in time series through time convolutional layers. Secondly, TCN is mainly applied to one-dimensional time series and cannot effectively utilize node relationships in graph structures. TGCN introduces a graph structure and combines the temporal information of each node and its neighbors to achieve more accurate temporal prediction and anomaly detection. The idea of the dynamic data accuracy detection method is shown in Figure 5.

As shown in Figure 5, considering data accuracy detection from both temporal and spatial dimensions, the results obtained from each are fused to complement each other's advantages, thus obtaining an accuracy detection method. The expression of spatiotemporal graph and loss function is shown in equation (7).

$$\begin{cases} G_t = (V_t, E, W) \\ L(\hat{v}, W_\theta) = \| \hat{v}(v_{t-M+1}, \cdots, v_t, W_\theta) - v_{t+1} \|^2 \end{cases} \tag{7}$$

In equation (7), G_t represents the spatiotemporal graph, V_t means the node set, E means the edge set, W means the adjacency matrix, $L(\hat{v}, W_\theta)$ represents the loss function, W_θ represents all trainable parameters, $\hat{v}$ represents the predicted value, and v_{t+1} represents the true value. Fourier transform has a broad spectrum of utilization in signal processing, image processing, audio processing, and other fields. It can decompose complex signals into the superposition of sine waves and cosine waves of different frequencies, which is extremely useful for signal analysis and processing. The Fourier transform process is shown in equation (8).

$$\begin{cases} Lx = U \lambda U^T x \\ L\left(L = D - A\right) \end{cases} \tag{8}$$

In equation (8), Lx represents the process of Fourier transform, x represents an n dimensional column vector representing the characteristics of nodes, D represents the degree matrix of the graph, U and U^T represent orthogonal matrices, and $L(\cdot)$ represents the Laplacian matrix of the graph. The calculation for the GCN obtained from the study is shown in equation (9).

$$X^{n+1} = \sigma(AX^n W) \tag{9}$$

In equation (9), X represents the feature matrix, and σ represents the nonlinear activation function. The

forward propagation process of GCN is described by equation (9), which utilizes graph structure information and node features to aggregate and update local neighborhood information of nodes through convolution operations. The calculation of one-layer TCN in TGCN is represented in equation (10).

$$\begin{cases} H(s) = \sum f(\cdot) XF(x) \\ F(x) = W\sigma(\cdot) + \alpha \end{cases} \tag{10}$$

In equation (10), $H(s)$ represents a layer TCN in TGCN, $f(\cdot)$ represents the convolution kernel, and $F(x)$ means the residual function. The loss function during the training process of TGCN model is represented in equation (11).

$$Loss = || X_c - \hat{X} ||_b + \lambda L_2 \tag{11}$$

In equation (11), *Loss* represents the loss function, X_c means the detection value of the model, $\hat{X}$ means the actual values of various detection attributes in the data, L_2 represents the regularization term of the model, and λ represents hyperparameters. The TGCN data accuracy detection method needs to test the core performance indicators before actual operation, and use the test results as a reference to optimize the method specifically and targetedly. The performance of TGCN method is evaluated using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), and the evaluation indicators are shown in equation (12).

$$\begin{cases} P_{RMSE} = \sqrt{\frac{1}{\gamma}\sum (\hat{\mathrm{X}}_{v_i}^{t+1} - \mathrm{X}_{v_i}^{t+1})^2} \\ P_{MAE} = \frac{1}{\gamma}\sum_{i=1}^{\gamma} | \hat{\mathrm{X}}_{v_i}^{t+1} - \mathrm{X}_{v_i}^{t+1} | \\ P_{MAPE} = \frac{1}{\gamma}\sum_{i=1}^{\gamma} \frac{| \hat{\mathrm{X}}_{v_i}^{t+1} - \mathrm{X}_{v_i}^{t+1} |}{\mathrm{X}_{v_i}^{t+1}} \end{cases} \tag{12}$$

In equation (12), $\mathrm{X}_{v_i}^{t+1}$ and $\hat{\mathrm{X}}_{v_i}^{t+1}$ represent the true and reference values of the property v_i of the object at time $(t+1)$, separately, and γ means the number of objects. P_{RMSE}, P_{MAE}, and P_{MAPE} represent RMSE, MAE, and MAPE, respectively. RMSE and MAE can reflect the error situation between the true value and the reference value, while MAPE can reflect the ratio between the error and the true value. In the comprehensive evaluation of algorithms, indicators such as accuracy and recall are often used to assess the rationality of the method. $f1\_score$ is considered a key indicator for measuring the effectiveness of accuracy detection, and its calculation is shown in equation (13).

$$\begin{cases} P = \frac{TP}{TP + FP} \\ R = \frac{TP}{TP + FN} \\ f1\_score = \frac{2 * P * R}{P + R} \end{cases} \tag{13}$$

In equation (13), P represents accuracy, R represents recall, $f1\_score$ represents the combined score of accuracy and recall, and TP means positive samples classified as correct by the model. FN means positive samples classified as incorrect by the model. FP refers to negative samples classified as incorrect by the model. In practical applications, the TGCN designed for research also involves parameter selection. The GCN parameter adjacency matrix usually uses a normalized adjacency matrix, and the number of GCN layers is generally 1-2 to avoid over smoothing. The activation function is often ReLU or LeakyReLU, and the dimension of the weight matrix depends on the dimensions of the input and output features. The learning rate is usually set to 0.001 or 0.0005, which can be optimized using a dynamic learning rate scheduler and L2 regularization to prevent overfitting. The batch size is set to 32, 64, or 128 based on the data size, and an early stop strategy is used during training to prevent overfitting based on performance monitoring of the validation set.

4 Analysis of the effectiveness of dynamic data detection methods in spatiotemporal data mining

4.1 Performance testing of dynamic data detection methods for spatiotemporal data mining

To analyze the ability of the multi-factor development dynamic data detection method established in the study during runtime, data from a network company was used as the test data. Compare the happen before algorithm (HAB) [19], Lockset algorithm (Lock) [20], and BufferTrack algorithm (Butra) [21] with TGCN to evaluate its data processing performance. The software and hardware environment required for the experiment is represented in Table 2.

To verify the effectiveness of SSA missing filling method, a 12-month workload data of a network company was selected as the dataset. The dataset contains the workload changes of the company within one year, with a size of approximately 8GB and six million data points. The data features cover multiple dimensions such as timestamp, request volume, response time, etc., which can help analyze the patterns and trends of network traffic. In the preprocessing step, the study first performed data cleaning, removing some obvious erroneous records and outliers; Then feature selection was carried out, retaining the most critical indicators for workload analysis; Then, the data was standardized to

enable comparison of data from different indicators at the same scale, in order to improve the effectiveness and accuracy of subsequent interpolation algorithms. Fourier interpolation method [22] and SSA method were applied to fill in the missing data. The filling results of the two methods are shown in Figure 6.

Table 2: System development and operating environment.

Project	Software and framework
Integrated development environment	Visual studio 2013
Database environment	SQL Server 2019
Operating system	Windows10, Linux
Framework	.NET, Mini UI
Programming language	C#, JavaScript
Web server	IIS 7.0
Network protocol	UDP, TCP/IP

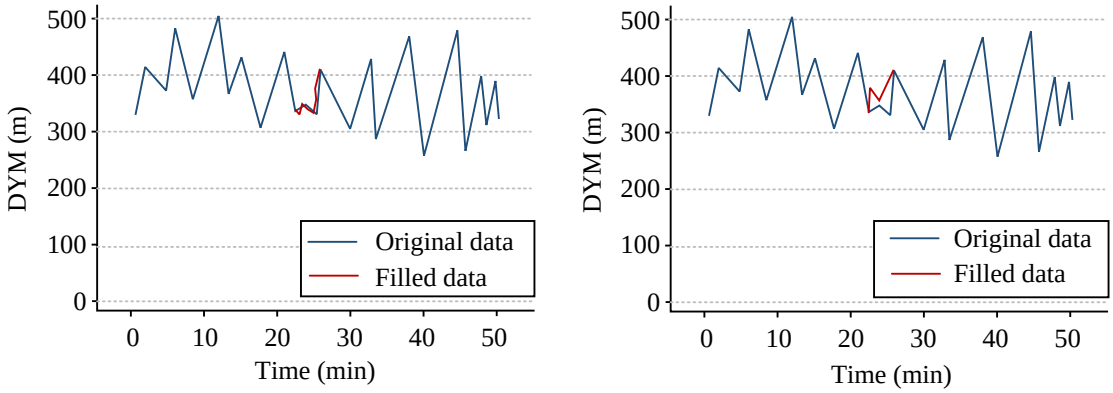


Figure 6: Comparison chart of two filling methods.

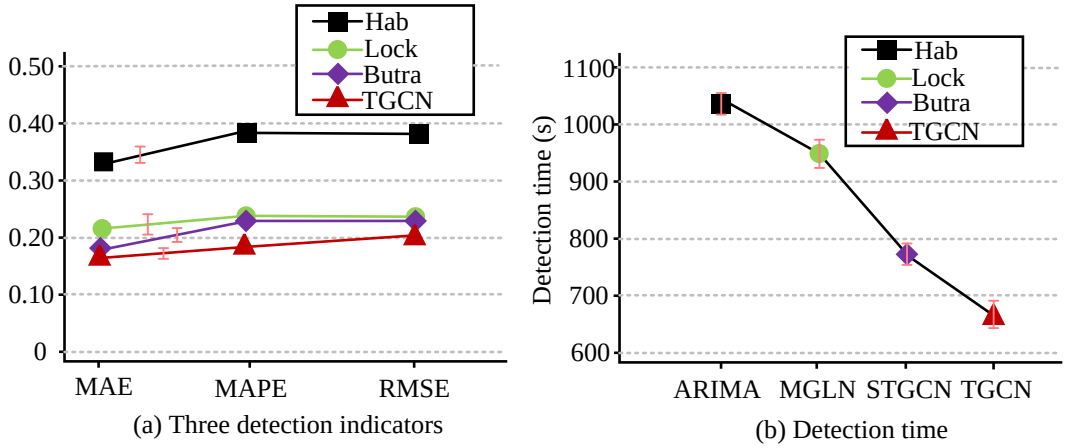


Figure 7: Analysis of performance indicators for different methods of operation.

Figure 6 (a) shows the use of SSA missing filling method to fill in the original data, while Figure 6 (b) shows the use of Fourier fast interpolation method to fill in the original data. As shown in Figure 6 (a), the SSA missing filling method effectively filled in missing data, and the filled data was closely aligned with the original data in the time series. It is worth noting that the DYM deviation of the SSA missing filling method was about 5 meters, indicating minimal deviation from the original signal. The smooth transition between interpolated values without obvious peaks or large fluctuations indicated that this method could accurately preserve the trends and features of the original dataset. From Figure 6 (b), in contrast, the Fourier fast interpolation method showed significant deviation, especially in the time interval of 20 to 30 minutes, where the DYM deviation rose to about 25 meters. This difference highlights that the method failed to accurately capture potential trends during this critical period. There were significant differences between the filled data and the original data, exhibiting unrealistic oscillations and leading to misunderstandings of data trends. The SSA missing filling method is more suitable for scenarios where maintaining consistency in the original data structure is crucial, while the Fourier fast interpolation method may introduce significant inaccuracies, especially when analyzing dynamic data where accurate trend representation becomes crucial.

Considering that the methods in Related Works have been optimized for specific preset scenarios, it cannot be guaranteed that the optimal learning performance can be fully reflected in the studied scenarios. So, the study compared three advanced methods with sufficient applicability, Hab, Lock, and Butra, to analyze the performance of TGCN by comparing Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and detection time. The Hab algorithm sets a fixed window size of 1024, uses 3 times the standard deviation as the anomaly threshold, and updates statistical features after each window is processed. The Lock algorithm defines a lock set containing 256 key data points, analyzes data at 30 second intervals, and configures specific CPU and memory resource allocation strategies to optimize execution efficiency. The Butra algorithm uses a dynamic buffer with an initial size of 2048, tracking data changes within the last 5 minutes and sampling data at a frequency of once per second to ensure real-time performance and reduce processing latency. TGCN sets 0.003 as the initial learning rate of the algorithm, 0.30 as the activation function parameter, 64 as the batch size, 120 as the number of network iterations, and 2 as the initial dilation factor in the time convolution module. The experimental results are shown in Figure 7.

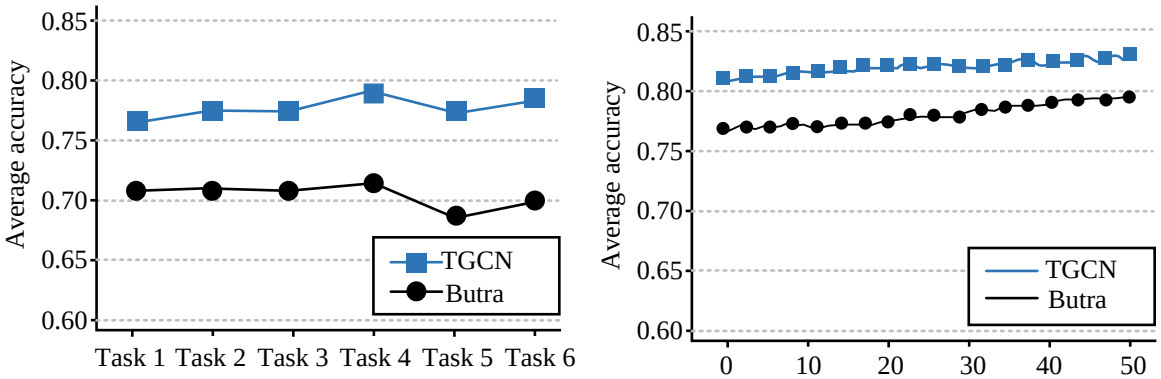
Figure 7 (a) indicates the behaviour of four methods tested using MAE, MAPE, and RMSE metrics, and Figure 7 (b) indicates the behaviour of the four methods tested using detection time. According to Figure 7 (a), the MAE, MAPE, and RMSE indicators of TGCN were the lowest among the four models, at 0.16, 0.18, and 0.20, respectively, lower than the other three comparison methods. However, the MAE, MAPE, and RMSE indicators of the Hab model were the highest among the four models, at 0.34, 0.39, and 0.38, separately. From Figure 7 (b), Hab had the longest detection time, at 1300 seconds, which was significantly longer than the other three comparison methods, while TGCN had the shortest detection time among the four methods, at only 670 seconds. From this, the TGCN model had the lowest detection indicators among the four models, followed by Butra, indicating that the TGCN model could shorten detection time and improve detection efficiency. Compared with the methods of Hab, Lock, and Butra, the research method had lower computational complexity. Unlike Hab's method, this approach typically involves deep architectures with multiple layers, simplifying feature extraction and focusing on fundamental aspects without unnecessary complexity. The Lock method tends to include redundant processing steps, while the research method uses SSA for denoising and missing data filling, which helps with clearer data processing and improves efficiency. In addition, although Butra's method combines multiple models to capture temporal and spatial features separately, the integrated model of the research method simultaneously solves these two problems and reduces processing time. Finally, the advanced optimization algorithms used in the research methodology allow for faster convergence and significantly reduce training time without sacrificing accuracy. Overall, these factors make research methods more efficient and suitable for real-time dynamic data applications. To further test the stability of TGCN, the Butra model with better performance in the above results was selected as the comparative model, and experiments were conducted under different detection tasks and experimental conditions. The experiment outcomes are represented in Figure 8.

Figure 8 (a) shows the average accuracy changes of TGCN and Butra under different detection task conditions, and Figure 8 (b) shows the average accuracy changes of TGCN and Butra under different experimental conditions. From Figure 8 (a), when TGCN processed different tasks, the average accuracy was relatively stable, maintaining in the range of 0.75-0.80, while Butra's average accuracy fluctuated greatly and was lower than 0.72. According to Figure 8 (b), as the number of experiments increased, the average accuracy of TGCN remained in the range of 0.80-0.85, while Butra's average accuracy fluctuated significantly, below 0.78. From this, TGCN had a high accuracy rate when processing different tasks, and the accuracy rate showed a basically stable trend as the number of experiments increased. In order to determine the effectiveness of different components in the research method, 70% of the data in the dataset was used for ablation experiments, as shown in Table 3.

As can be seen, the Baseline Model demonstrated the best performance with a best accuracy of 97.00%, a recall of 95.00%, and an F1 score of 96.00%, indicating the combined model performed exceptionally well in dynamic data detection tasks. Removing SSA resulted in a decrease in the best accuracy to 94.50%. SSA played a vital role in filling missing data, and its absence led to data incompleteness, negatively impacting the recall rate and F1 score. The removal of GCNN resulted in the most significant performance drop, with the best accuracy plummeting to 92.00%. GCNN was essential for extracting spatial features from the data, and losing this component severely affected the model's ability to handle complex data. The model's performance only slightly declined when TCN was removed, achieving a best accuracy of 93.50%. This suggests that while temporal feature extraction had some impact, it was comparatively less critical than spatial features. With the removal of Fourier Transform, the best accuracy dropped to 95.00%, indicating the importance of Fourier Transform in extracting frequency-domain features. Finally, removing Spatiotemporal Recombination resulted in a performance decline to 93.00%. Although spatiotemporal recombination enhanced the model's ability to capture spatiotemporal data, its impact was relatively smaller than that of other components.

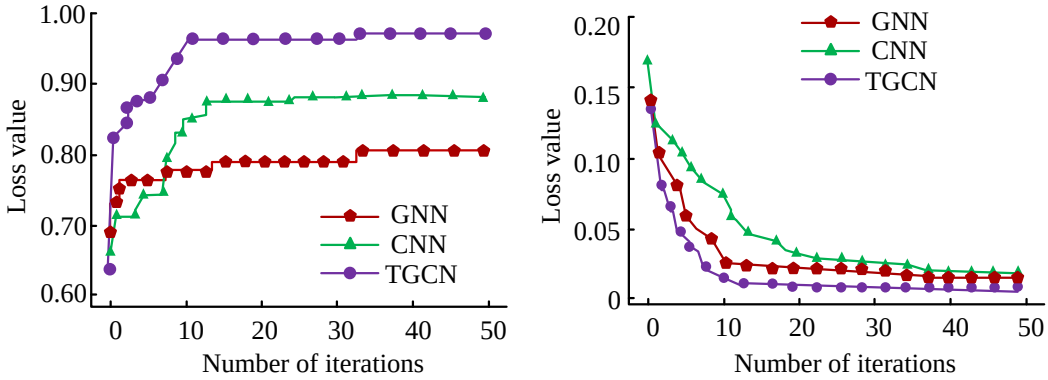
Table 3: Ablation experiment

Component	Best accuracy (%)	Recall (%)	F1 Score (%)
Baseline Model (All)	97.0	95.0	96.0
Remove SSA	94.5	92.0	93.2
Remove GCNN	92.0	90.0	91.0
Remove TCN	93.5	91.5	92.3
Remove Fourier Transform	95.0	93.5	94.2
Remove Spatiotemporal Recombination	93.0	90.5	91.7



(a) Detection task category (b) Number of tests

Figure 8: Average accuracy fluctuation analysis.



(a) Accuracy (b) Error rate

Figure 9: Comparison of accuracy and misjudgment rate of three methods.

4.2 Application analysis of dynamic data detection methods in spatiotemporal data mining

To further demonstrate the advantages of the proposed method in dynamic data monitoring, the accuracy and misjudgment rates of TGCN and CNN [23], GCN [24] were compared. The accuracy of the detection here was obtained during the monitoring process of a large amount of data, so it tended to approach a specific value rather than a special numerical range obtained for a specific individual task. The accuracy and misjudgment rates are represented in Figure 9.

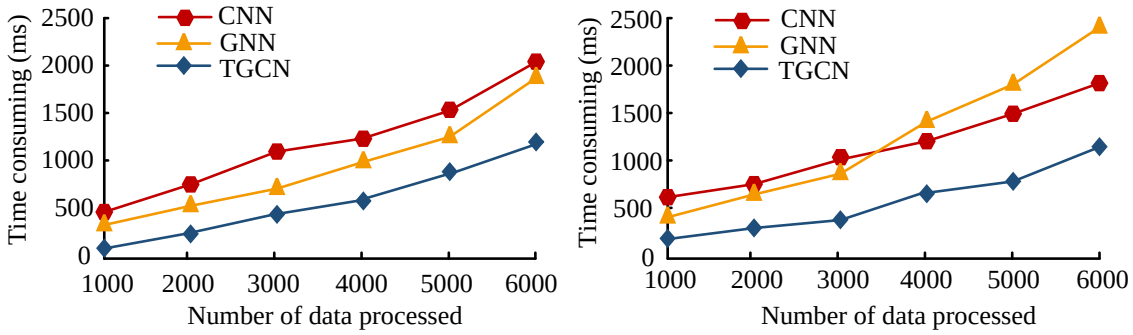
Figure 9 (a) shows the accuracy comparison at different iteration times, and Figure 9 (b) shows the false positive rate comparison at different iteration times. As represented in Figure 9 (a), the accuracy of TGCN was stable at 0.97, the accuracy of CNN was stable at 0.88, and the accuracy of GNN was only 0.81. It is told that the accuracy performance of TGCN was good. According to Figure 9 (b), as the number of iterations increased, the false alarm rates of all three methods decreased. Among them, TGCN decreased from the initial 0.14 to 0.01, which was significantly lower than the other two compared algorithms. TGCN could improve the accuracy of data detection process and reduce false alarm rate, thus achieving dynamic data detection. The attendance data of two departments in a company for 12 months were analyzed, the time under different data volumes was calculated, and the results are represented in Figure 10.

Figure 10 (a) compares the processing time of three methods for different sizes and quantities of data in Department A, and Figure 10 (b) compares the processing time of three methods for different sizes and quantities of data in Department B. From Figure 10 (a), it is told that for Department A, the TGCN method required a processing time of 250 ms when processing

2000 data points, and 1000 ms when processing 6000 data points. For the same amount of data, the processing time of TGCN was the shortest, and as the amount of data increased, the required processing time also increased. According to Figure 10 (b), for Department B, the TGCN method required a processing time of 300 ms for 3000 data points and 750 ms for 5000 data points, which was lower than the other two comparison algorithms. For the same amount of data, TGCN had the shortest processing time, and as the amount of data increased, the required processing time also increased. Comparing the data processing volume before and after applying TGCN at different times, the application results in two departments are represented in Figure 11.

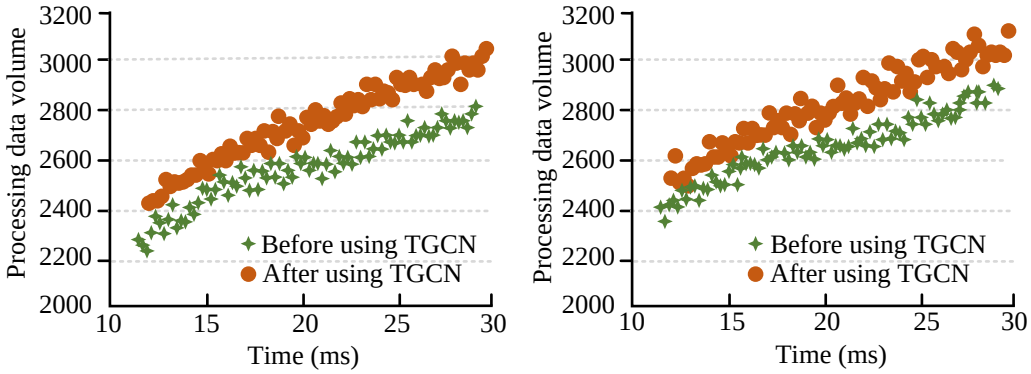
Figure 11 (a) tells the amount of data processed by department A before and after applying TGCN at different times, while Figure 11 (b) tells the amount of data processed by department B before and after applying TGCN at different times. According to Figure 11 (a), for Department A, before and after using the TGCN method, the data processing increased from around 2500 to around 2600 within 15ms, and from around 2800 to 3000 within 30ms. According to Figure 11 (b), for Department B, before and after using the TGCN method, the data processing increased from around 2500 to around 2700 within 15ms, and from around 2900 to 3100 within 30ms. Using the TGCN method within the same time frame can accelerate data processing speed and improve efficiency. In order to further analyze the advantages and scalability of the research method, an online social networking platform was selected for real-time data detection, and the advanced K-nearest neighbor interpolation method [25] and polynomial interpolation method [26] in recent years were introduced for comparison, as shown in Table 4.

As shown in Table 4, the RMSE of TGCN method was 5.0 meters, significantly lower than K-nearest neighbor interpolation method (12.0 meters) and polynomial interpolation method (15.0 meters), indicating that TGCN method had significant advantages in filling accuracy. The relative error of TGCN method was only 1.2%, which was the lowest among all comparison methods, highlighting its superiority in data filling. The detection time of TGCN was only 1.1 seconds, which was lower compared to other methods. The cosine similarity of TGCN method was 0.95, indicating a high degree of consistency between the filled data and the original data. In contrast, the K-nearest neighbor interpolation method had a similarity of 0.80 and the polynomial interpolation method had a similarity of 0.75, indicating that its similarity was not as good as the TGCN method. After comparison, TGCN had the shortest detection time and the best detection accuracy, and its good performance in different data scenarios also proved the good scalability of the research method.



(a) A department (b) B department

Figure 10: Calculation time for processing different data.



(a) A department (b) B department

Figure 11: Processing data volume at different times.

Table 4: Comparative analysis of advanced methods

Method	TGCN	K-nearest neighbor interpolation method	Polynomial interpolation
RMSE (m)	5	12	15
MAPE (%)	1.2	3	4.5
RE (%)	1.2	2.5	3.5
MAE (m)	10	20	25
Detection time (seconds)	1.1	1.7	1.2
Cosine similarity	0.95	0.8	0.75
Data consistency (%)	98	92	90
Interpolation smoothness (m/min)	0.3	0.8	1

4.3 Discussion

The study proposes a method based on TGCN, combining GCNN and TCN, to achieve accuracy detection of dynamic data. Compared with traditional methods in related work, TGCN exhibits significant advantages in efficiency, accuracy, and robustness. Firstly, in terms of efficiency, traditional methods such as autoregressive models and moving average models often rely on linear regression and simple statistical methods for data processing, resulting in slower processing speeds. Relatively speaking, TGCN adopts deep learning technology and can process massive amounts of data in parallel. Experimental results showed that this method only took 670 seconds in detection time, which often took several hours to achieve in traditional models. This significant time advantage makes TGCN a more attractive choice in real-time data monitoring applications. Secondly, in terms of accuracy, compared with threshold-based anomaly detection methods, TGCN can simultaneously consider the temporal and spatial characteristics of data by introducing time-series analysis. Many methods in related work often have an accuracy of only around 0.85 when dealing with outliers, which cannot effectively handle complex data streams. The TGCN in this study improved the accuracy of detection by combining singular spectrum analysis, and the experimental results showed that its accuracy remained stable above 0.97. This optimization enables TGCN to maintain efficient anomaly detection capabilities even in the face of dynamically changing data. In terms of robustness, some existing methods are often sensitive to noise and data loss, leading to fluctuations in detection results. TGCN, through its deep network structure, has strong adaptive capabilities and exhibits better adaptability to interference in dynamic data. In the experiment, TGCN showed improved robustness when dealing with noisy data, resulting in significantly higher accuracy and stability of the model in complex environments compared to many related works. Although the TGCN method in this study achieved excellent performance in multiple aspects, its limitations cannot be ignored. The training cycle of the model was relatively long, especially in real-time processing of large-scale datasets, which may face a bottleneck in computing resources. In addition, TGCN had poor interpretability in practical applications, which may make it difficult for business personnel to understand the decision-making logic of the model. Future research can explore the integration of interpretable online artificial intelligence technology into the TGCN model, thereby enhancing its interpretability and user trust. In addition, in order to support real-time data detection tasks on large-scale datasets, it is necessary to develop a distributed computing framework to further enhance the scalability of the model.

5 Conclusion

A dynamic data detection technique based on spatiotemporal mining technology was developed to enhance data processing in the network. During the process, the singular spectrum analysis method was introduced to fill in missing data, and the spatiotemporal topology structure was fused to establish a dynamic data detection method. A data accuracy detection method was proposed by combining GCNN and TCN to complete the data accuracy detection. The data was detected in both the temporal and spatial dimensions, and the two were added together to obtain complete detection data. Finally, the validity of the raised method was analyzed. The experiment outcomes indicated that in terms of data filling, the SSA missing filling method used in the study was more in line with the original data curve for filling missing data. In terms of false positive rate, the method proposed by the research decreased from 0.14 to 0.01, which was lower than the two compared methods. As the number of iterations increased, the false positive rate gradually decreased. In terms of processing speed, before and after using the TGCN method, the data processing time increased from around 2500 to 2700 within 15 ms, and from around 2900 to 3100 within 30 ms. The research method had better data filling effect on missing data, which could process data at a higher speed and ensure stable accuracy at a higher level.

6 Fundings

The research is supported by National Social Science Foundation of China in 2022: Research on Evaluation System and Guarantee Mechanism of Labor Rights and Interests of Flexible Employees in Platform Enterprises (22XJY004).

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Fusion CNN-Transformer Model for Target Counting in Complex Scenarios

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Keywords: convolutional neural network, attention mechanism, computer counting, target counting, fully self attention network

Received: October 12, 2024

To overcome the shortcomings of traditional manual counting methods, which are labor-intensive, resource-consuming, and inefficient, this study introduces a computer-based counting model. This model integrates convolutional neural networks (CNNs) with Transformer networks to efficiently recognize and count specific target objects in large-scale data scenarios. This approach leverages CNNs for local feature extraction and incorporates Transformer networks to capture long-range global information, achieving a synergistic effect. The methodology includes key steps such as "CNN for feature extraction and Transformer for global attention." The experiment outcomes show that the model has an average absolute error of 10.13, a root mean square error of 12.08, an average counting accuracy of 98.6%, a peak signal-to-noise ratio of 23.75, a structural similarity of 0.933, a coefficient of determination of 0.901, an average counting time of about 6.58ms per image, and a parameter count of 3.21 in target counting. It can also recognize and respond well to high complexity scenes while maintaining high accuracy. Compared to the CNN model, the research model reduces the error rate by 13.4%, indicating that the fusion of CNN and Transformer networks is effective in object counting for computer vision tasks. This result indicates that the model integrating convolutional neural networks and fully self attention networks can be well applied to computer recognition and object counting.

Povzetek: Predstavljen je hibridni model CNN-Transformer za štetje tarč v kompleksnih scenarijih. Model združuje CNN za ekstrakcijo lokalnih značilnosti in transformer za zajemanje globalnih informacij.

1 Introduction

Traditional counting relies on manual operation, with low processing power and efficiency, and often requires a lot of manpower and time to identify large-scale data [1-3]. However, as computer technology advances, in recent years, many researchers have begun to rely on computer vision technology to handle the matter of object detection and identification counting in the context of big data. At present, the application of computer counting has spread to many fields, such as road vehicle recognition and counting in vehicle transportation systems, melon and fruit counting in large-scale agricultural and forestry production, livestock counting, and colony counting in laboratories, etc. [4-5]. With the advancement of computer vision technology, an increasing number of computers counting algorithms and models have been developed and applied. Leong J M et al. developed a fish counting system based on convolutional neural network (CNN) to assist hatchery staff in counting fish from images. During the process, contrast limited adaptive histogram equalization was also used to enhance the captured images, and a YOLOv5 form of deep learning architecture was incorporated to generate a model that can recognize and compute fish on the images. The experimental results showed that the recall rate of the model reached 65.5% [6]. Chen G et al. proposed a new efficient deep learning model called Density Transformer for automatically counting trees from aerial images. This architecture includes a multi-receptive field CNN for extracting visual feature representations from local patches and their extensive contexts, and a Transformer encoder for transmitting contextual information between relevant locations. The experimental results showed that the research model achieved the highest accuracy on both datasets, significantly better than most other methods [7]. Miao Z et al. proposed a weakly-supervised method that effectively combines multi-level dilated convolution and Transformer methods to achieve end-to-end crowd counting. The experimental results showed that on four well-known benchmark population counting datasets, this method outperformed other weakly supervised methods and was comparable to fully supervised methods [8]. Liu et al. proposed a multi-receptive field extraction deep learning method grounded on YOLOX

(MRF-YOLO) for detecting and counting small targets, and validated it on the cotton bolls dataset of a cotton farm. The results indicated that the average accuracy of the model rose by 14.86%, with a mean square error of 1.06 and a coefficient of determination of 0.92. The model could be well applied to a wide range of small target crop detection [9]. Shen L et al. constructed a YOLOv5s cluster detection model grounded on channel pruning algorithm and applied it to counting grape clusters in the field. The research results showed that the mAP reached 82.3%, the average inference time per image was 6.1 ms, the average counting accuracy was 84.9%, the video processing speed was 50.4 frames per second, and the model parameters and complexness were effectively reduced while guaranteeing perception precision. This model could be well applied to counting stacked grape clusters [10].

Despite the notable achievements of the aforementioned studies in their respective application scenarios, the field of computer counting still faces several challenges and limitations. In particular, mainstream models like YOLO frequently produce false positives and negatives when confronted with small, densely packed targets, largely attributed to their limited capacity in managing complex scenes and dealing with target occlusion. Furthermore, many existing counting models struggle to balance local and global feature information. Local features are crucial for accurately identifying individual targets, while global features aid in understanding the entire scene and the distribution of targets. However, existing models often fail to achieve a balance between the two, resulting in insufficient flexibility and accuracy during counting.

In response to these limitations, this study proposes a computer counting algorithm that integrates CNN and Transformer networks. This algorithm aims to combine the advantages of CNNs in local feature extraction with the capabilities of Transformers in global feature capture and sequence modeling, thereby enhancing the accuracy and flexibility of computer counting. By introducing the Transformer module, it is hoped to enhance the model's understanding of global contextual information while leveraging the convolutional operations of CNNs to precisely capture the local features of targets. This fusion strategy is expected to address the shortcomings of existing models when dealing with small and densely packed targets, while also improving the counting performance of the model in complex scenarios.

2 Methods and materials

2.1 Counting algorithm integrating CNN

Computer counting refers to the collection of information through computer vision mechanisms, in order to achieve the effect of calculating or counting quantities. This method is often applied in the area of image processing, such as vehicle counting, crowd counting, cell counting, etc. CNN, as a type of deep learning algorithm, is commonly applied in image recognition in the area of computer vision. It simulates the way neurons in the human brain process information, especially the working mode of the visual cortex, and abstracts and extracts feature layer by layer from input data to achieve automatic processing and recognition simulation of grid structured data such as images [11-12]. These features provide detailed object and element information for subsequent counting tasks. CNN is mainly composed of three parts: convolutional layer, pooling layer (also known as downsampling layer), and fully connected layer. Its structure is represented in Figure 1.

In Figure 1, the first layer performs convolution operation on the input image to get a feature map (FM) with a depth of 3. Then pooling operation is constructed on the obtained FM to get a novel FM. The convolution pooling joint operation will be repeated until an FM with a depth of 5 is obtained. This operation process can extract input data features layer by layer. As the number of convolutional and pooling layers rises, the model's ability to interpret and express data gradually improves. Finally, the obtained latest round of FMs is expanded and connected into vectors by rows, and passed into a fully connected layer. the internal hierarchical structure of CNN is analyzed. Part 1: convolutional layers, as shown in formula (1).

Table 1: Literature review table.

Literature	Method	Major contribution	There are problems
Leong J M et al. [6]	CNN-YOLOv5	Assist the staff of the hatchery in counting fish from the images	The recall rate of the model is not high
Chen G et al. [7]	Deep learning models, a multi receptive field CNN	Can achieve automatic calculation of trees in aerial images	The accuracy value is only slightly higher than the general model
Miao Z et al. [8]	Weak supervision law, Transformer	Effectively combining multilevel expansion convolution and Transformer methods to achieve end-to-end population counting.	The research dataset is limited to the population, and the generalization application of counting methods still needs to be considered
Liu et al [9]	YOLOX（MRF-YOLO）	Design proposes a multi receptive field extraction deep learning method for detecting and counting small targets	Mean square error is relatively high
Shen L et al. [10]	YOLOv5s cluster detection model	constructed a detection model and applied it to the counting of grape clusters in the field.	The average counting accuracy is slightly lower and the inference time is slightly longer

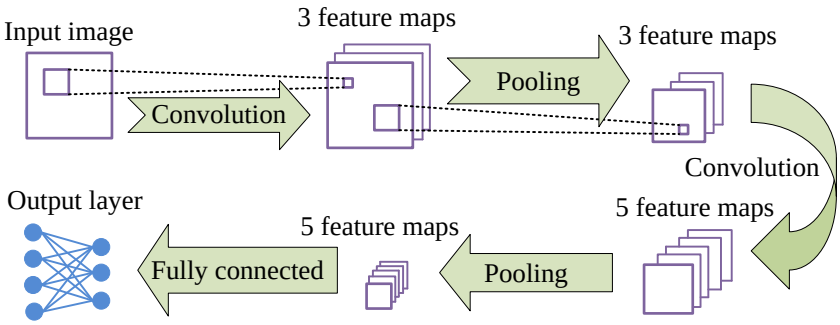


Figure 1: CNN structure diagram.

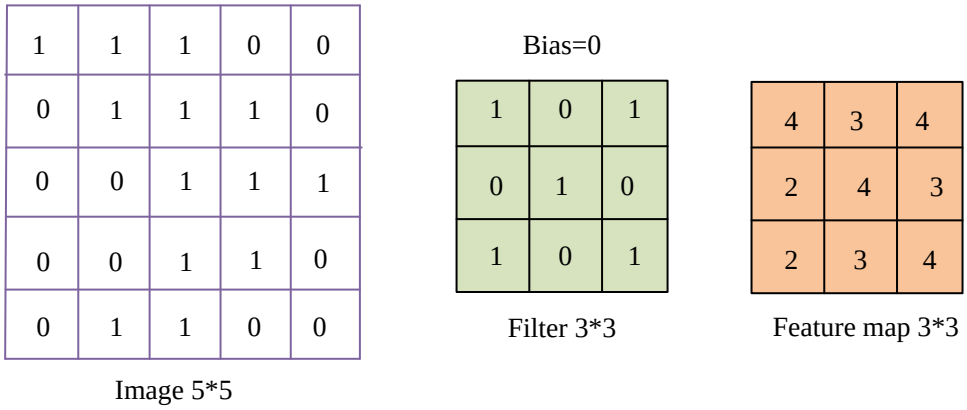


Figure 2: Example of convolution operation.

$$s(i,j)=(X*W)(i,j)=\sum_m\sum_n x(i-m,j-n)w(m,n) \quad (1)$$

$$X'=\frac{(X+2p-W)}{k}+1 \quad (2)$$

Formula (1) represents two-dimensional convolution. Among them, W is the convolution kernel (also known as the weight matrix or filter), X is the input matrix (also known as the input FM), and $s(i,j)$ means the value of the output matrix at position (i,j). $w(m,n)$ means the value of convolution kernel W at position (m,n). $x(i-m,j-n)$ represents the elements of the input matrix X that are accessed in the convolution operation. * Represents convolution. The essence represented by this formula as a whole is to multiply and add the elements at different positions of the matrix and convolution kernel matrix of different parts of the image, as shown in Figure 2.

Figure 2 gives an illustration of convolution process. An image is input and converted into a matrix. In the example, the matrix corresponding to the image is 5×5, and a 3×3 convolution kernel is utilized for convolution to acquire a 3×3 FM. However, not all sliding steps are 1 and need to be adjusted according to the situation. If the sliding stride is greater than 1, there may be a situation where the convolution kernel cannot slide exactly to the edge. In this case, it is necessary to add zeros to the outermost layer of the matrix, as shown in formula (2).

In formula (2), the strid is k and the zero-padding layer is p. The second part is pooling. The pooling layer cuts the dimensionality of FMs while preserving important details through downsampling operations. Pooling can be divided into two types: maximum pooling and average pooling. Compared to max pooling, average pooling can preserve more detailed information. The third part is the fully connected layer, as shown in formula (3).

$$\begin{cases} Y=\varphi(V) \\ V=conv2(W,X,"valid")+b \\ E=\frac{1}{2}\left\|d-y^L\right\|_2^2 \end{cases} \quad (3)$$

In formula (3), *conv* represents the convolution function, *valid* represents the type of convolution operation, b is the bias vector, φ is the activation function, E is the total error, d represents the expected output vector, y means the output node vector, and L means the amount of layers. Figure 3 shows a fully connected diagram.

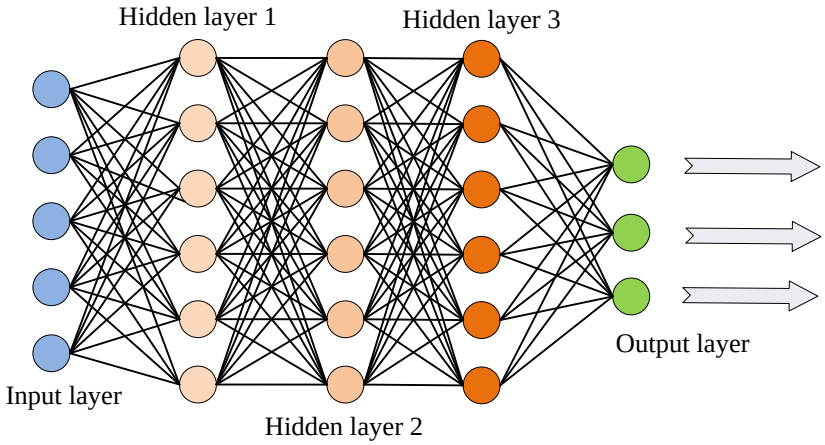


Figure 3: Fully connected layer operation process.

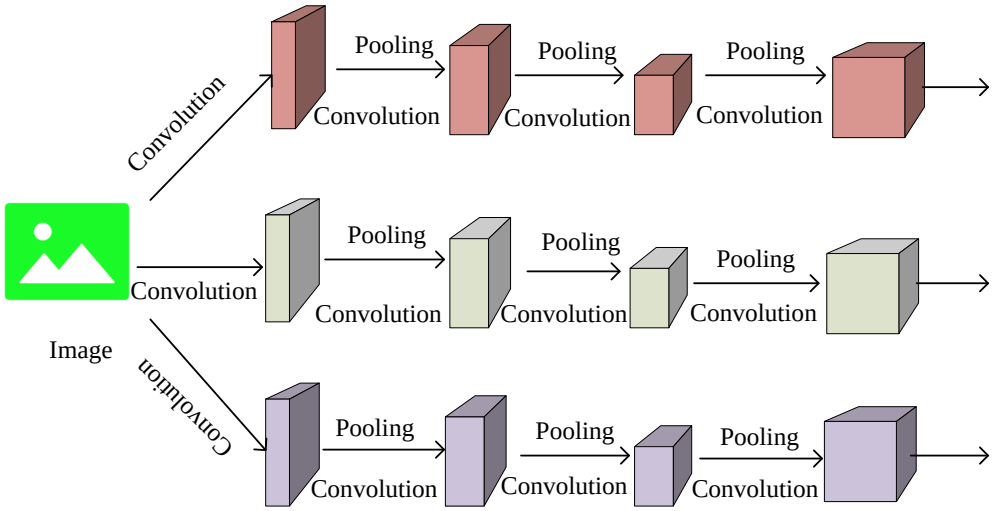


Figure 4: Network structure of FE module.

Figure 3 illustrates the classification function of the fully connected layer, which takes all local detail features as input to the input layer, passes through multiple hidden layers (including linear transformation, nonlinear activation, etc.), and finally generates prediction results through the output layer. However, when CNN is integrated with counting algorithms, it mainly focuses on FE and classification [13]. When the object overlap and coincidence rate of the counted image are high, it is very easy to encounter the problem of varying visual perception depth in comparison with the initial image, which makes it difficult to recognize or misidentify [14]. The counting algorithm that integrates CNN can improve the FE module of the original counting algorithm, helping to enhance the algorithm's ability to capture feature information, as shown in Figure 4.

Figure 4 gives the structure of the FE module that integrates CNN counting algorithm. The FE module includes three parallel CNN networks, with each column's filter (i.e. convolution kernel) having a different size of local receptive field. This produces different feature information extraction effects for counting objects of different distances and sizes, providing higher quality FMs for subsequent network modules and ultimately improving the quality of the algorithm's counting results. In short, integrating the powerful FE capabilities of CNN can effectively enhance computer vision technology and achieve automatic counting of specific objects in images or videos.

2.2 Counting algorithm integrating CNN transformer

Although CNN has strong local FE and parameter sharing capabilities, it can decrease the amount of model parameters and is widely used in image classification and object detection, thereby improving computer vision counting. However, CNN based counting algorithms lack modeling of global information, and CNN assumes that image features have spatial invariance. Therefore, once the target object undergoes deformation or positional changes, it will affect the final counting results [15]. Based on this, the study intends to introduce Transformer on the basis of CNN's counting algorithm. Transformer excels in global information modeling, complementing CNN and Transformer to raise the precision and validity of counting tasks, as represented in Figure 5.

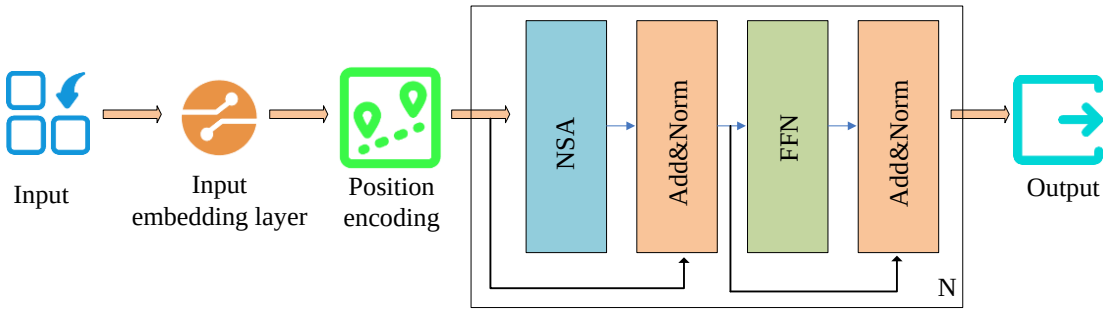


Figure 5: Schematic diagram of transformer structure.

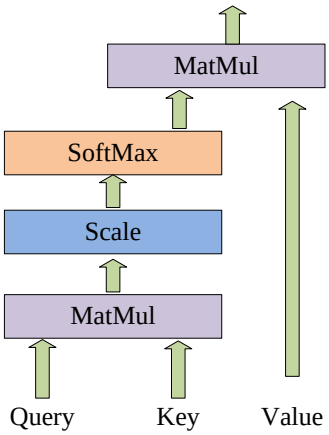


Figure 6: Self attention mechanism calculation process.

From Figure 5, it can be seen that Transformer is mainly composed of Position Embedding, Multi-Head Self Attention (MSA) mechanism, Residual Structure (Add), Normalization (Norm), and FeedForward Network (FFN) [16]. The entire processing flow is to first feed the input data into an input embedding layer composed of transition matrices and convert it into an initial tensor. Then positional encoding information is added to the tensor to generate a new tensor. The new tensor is immediately transmitted to the FE module for further processing. In the FE module, the FE process is repeated N times, each iteration aims at extracting deeper and more abstract characteristics from the input data, ensuring that the model can seize intricate patterns and structures in the data until the optimal result is output. Among them, the position code is shown in formula (4).

$$\begin{cases} PE_{(position,2i)} = \sin\left(\dfrac{position}{10000^{\frac{2i}{d_m}}}\right) \\ PE_{(position,2i+1)} = \cos\left(\dfrac{position}{10000^{\frac{2i}{d_m}}}\right) \end{cases} \tag{4}$$

In formula (4), PE is the position encoding, and the system in formula (4) is the commonly used position encoding, namely sine cosine position encoding. It represents the relative or absolute positional relationship between pixels. The function of position encoding is to enable the model to obtain effective position information. Among them, *position* represents the position of the input element, i means the specific dimension of the element, and d_m represents the dimension of the input. The Transformer model's essential feature is the self-attention mechanism, enabling it to consider all other elements while processing a single element in the sequence, thereby capturing long-range dependencies in the sequence. The computation process is shown in Figure 6.

In Figure 6, it can be seen that *Query*, *Key*, and *Value* are matrices composed of vectors q_i, k_i, and v_i. *Query* and *Key* obtain an output vector sequence containing rich contextual information through matrix multiplication, scaling, SoftMax, and quadratic matrix multiplication, while *Value* directly outputs the sequence through matrix multiplication. The specific first step calculation is shown in formula (5).

$$a_i = Wx_i \tag{5}$$

In formula (5), a_i is the middle tensor, W is the learning matrix, and x_i is the input tensor. Each input tensor is first multiplied by a W matrix and encoded to obtain the intermediate tensor. Multiplying each intermediate tensor with different learning matrices yields the desired vector, as shown in formula (6).

$$\begin{aligned} &q_i = W_q, \quad a_i k_i = W_k, \\ &a_i v_i = W_v a_i, \quad (i = 0,1,2,...,d) \end{aligned} \tag{6}$$

Among them, q_i , k_i , and v_i represent the vectors corresponding to Query, Key, and Value. W_q , W_k , and W_i are corresponding learnable matrices. d is the dimension of the input vector. Among them, each vector q_i will perform attention calculation on each vector k_j (j=0, 1, 2,..., d), that is, perform similarity calculation of vector dot multiplication. Due to the fact that the dot multiplication result increases with the increase of dimension, it is necessary to compress the result and process it through Sofmax, as shown in formula (7).

$$\begin{cases} a_{i,j} = Soft\max(\dfrac{q_i \cdot k_j}{\sqrt{d}}) \\ Soft\max(y_i) = \dfrac{e^{y_i}}{\sum e^{y_i}} \end{cases} \tag{7}$$

In formula (7), $a_{i,j}$ represents the normalized probability value of the vector at position (i, j) corresponding to the Softmax function processing. The Softmax function can convert the output values of multiple classifications into a probability distribution within the range of (0,1) and equal to 1. Finally, multiply the obtained a_{ij} with all vi vectors and sum them to obtain the feature pixels, as shown in formula (8).

$$Attention(Q,K,V) = Soft\max(\frac{QK^T}{\sqrt{d}})V \tag{8}$$

Formula (8) represents the calculation of attention weights in the self attention mechanism. It is worth noting that the current attention mechanism of Transformers usually adopts the Multi Head Self Attention (MSA) mechanism, which is represented as formula (9)

$$\begin{cases} Z_i = Attention(Q_i, K_i, V_i), \quad (i = 1,2,...,h) \\ MultiHead(Q,K,V) = Concat(Z_1, Z_2, ..., Z_h)W_o \end{cases} \tag{9}$$

In formula (9), i represents the i th self attention head, h means the amount of self attention heads, and Z_i means the output matrix calculated by the i th self attention head. Compared with self attention mechanisms, multi-head attention mechanisms can independently and parallelly compute attention in different subspaces, achieving the effect of simultaneously focusing on different features of the input sequence from different perspectives. In addition, in the normalization selection of the model, Transformer adopts layer normalization, as shown in formula (10).

$$LayerNorm(x) = \gamma \cdot (\frac{x-\mu}{\sigma}) + \beta \tag{10}$$

In formula (10), x represents the mean of the input tensor, μ is the standard deviation, γ and β represent learnable parameters, and the size is usually equal to the number of channels. Layer normalization is only applicable to single sample processing and is suitable for handling long sequence data and learning global relationships from single samples. In addition, residual connections are also introduced in the Transformer module, as shown in formula (11).

$$F = Att(X) + X \tag{11}$$

In formula (11), Att represents the attention layer and F represents the output feature. The function of residual connections is to send the data from the last layer to the subsequent layer through skip connections, which simplifies the model's learning process of identity maps, thereby promoting information flow and alleviating the problems of gradient vanishing and exploding [17-18]. In summary, integrating CNN and Transformer networks to construct CNN Transformer counting algorithms can complement each other's strengths and weaknesses, improve computational flexibility, enhance global information modeling capabilities, and improve the accuracy and efficiency of counting tasks. The detailed parameter information of the model is as follows, as shown in Table 2.

3 Results

3.1 Performance analysis based on CNN-transformer counting algorithm model

To verify the capability of the model grounded on the CNN-Transformer counting algorithm, simulation experiments were conducted for validation. Common computer vision applications include counting road vehicles in traffic monitoring systems and counting bacterial colonies in laboratory culture dishes. Considering the difficulty of obtaining the dataset, the study intended to use the actual chicken feeding situation of a large-scale breeding farm in a certain area as the experimental dataset. The selection of live chicken feeding data for this large-scale breeding farm was mainly based on the following considerations: Firstly, this dataset has high practical application value and can provide strong support for precision breeding and animal health management. Secondly, compared to other scenarios, the chicken flock activities in the breeding farm are more intensive and regular, providing rich test samples for counting algorithms. Finally, the dataset exhibits high diversity in terms of image quality, lighting conditions, and background complexity, which helps to comprehensively evaluate the model's generalization ability. A total of 80 live data segments were collected, with a duration of 30-60 seconds per segment, a resolution of 1920 × 1080 pixels, and a frame rate of 25 frames per second. For the collected chicken breeding video data, images were extracted from the video at intervals of 15 frames. In order to improve the quality of

the dataset, manual inspection was used to remove excessively similar or blurry images, and data augmentation was performed on the images in the training set, including random rotation, scaling, cropping, and color transformation. In addition, to ensure the accuracy of annotation, the study adopted cross validation method, where multiple annotators independently annotate the images and ensure the annotation quality through consistency checks. Finally, 761 images were obtained, and the dataset was separated into a training set (685 images) and a testing set (76 images) in a 9:1 ratio. The parameter size was set to: Learning Rate: 0.0005; Optimizer: AdamW; Epochs: 100; Batch Size: 32. The flowchart of data processing is shown in Figure 7.

Table 2: model parameters.

CNN			
Image size	Convolutional kernel size	Number of convolution kernels	Step size and filling
224×224×3	3x3	64	1
Transformer			
Embedding dimension	Position encoding	Hidden layer dimension	Encoder layers
768	Sine/Cosine Position Encoding	2048	6

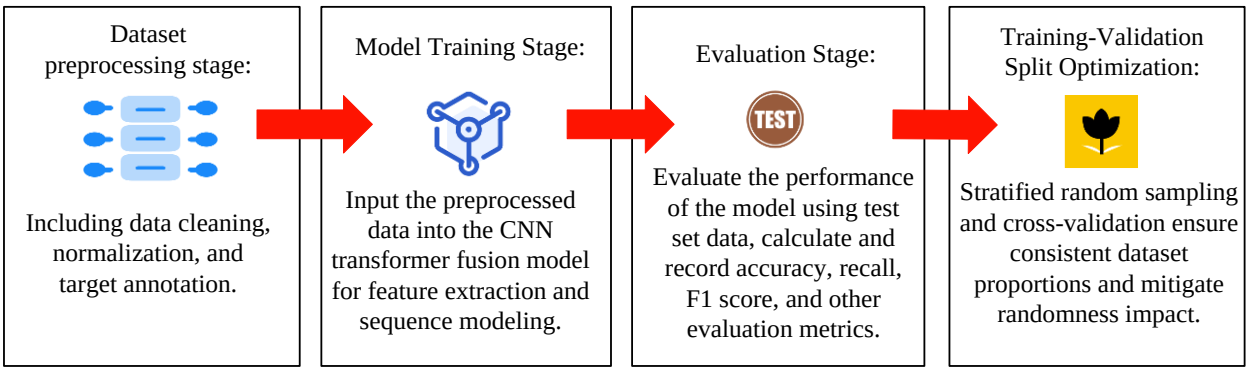
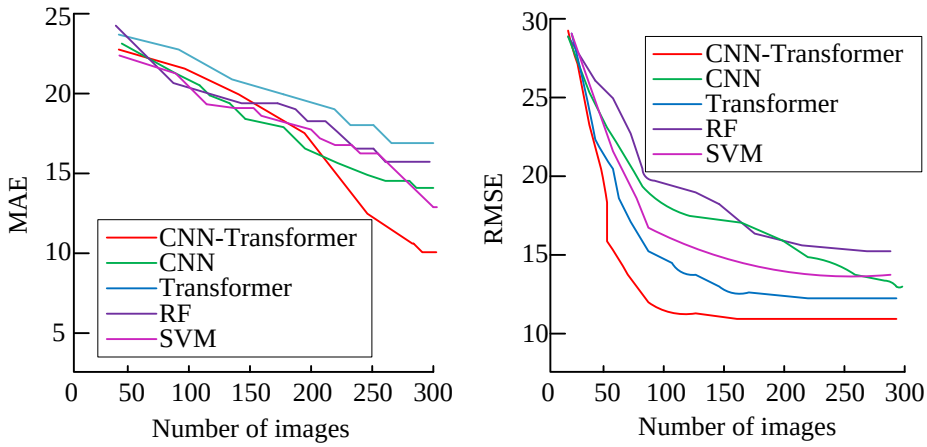


Figure 7: The flowchart of data processing.



(a) Performance indicators MAE of each model

(b) Performance of each model on the RMSE performance metric

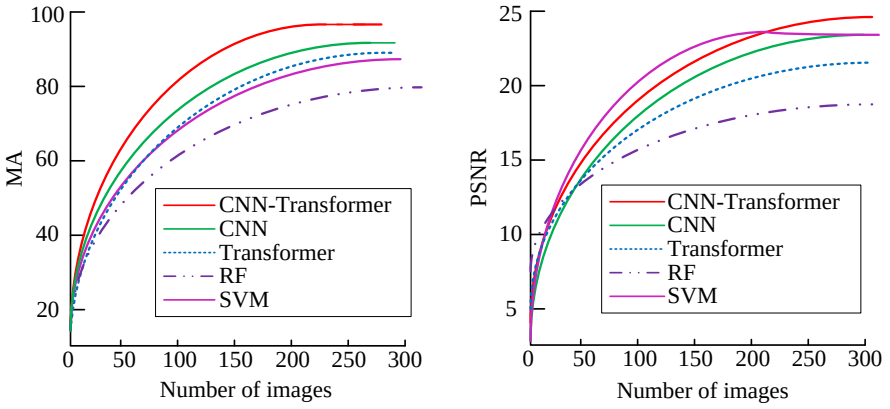
Figure 8: Performance of different algorithms on MAE and RMSE of the training set.

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Accuracy (MA), Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), and Coefficient of Determination (R2) were used as evaluation metrics for model performance. MAE measures the average of the absolute differences between the predicted and actual values. In counting tasks, MAE provides a straightforward reflection of the accuracy of the model's predictions. RMSE assigns higher weights to larger errors, in counting tasks, it highlights significant deviations in predictions. PSNR in counting tasks, it can be used to measure the similarity between the reconstructed count image and the actual count image. A higher PSNR value indicates better quality of the reconstructed count image and its closeness to the actual image. To more intuitively testify the superiority of the CNN Transformer counting algorithm model, four counting algorithm models including CNN, Transformer, Support Vector Machine (SVM), and Random Forest (RF) were included as comparative algorithms. The comparison results of MAE and RMSE performance of

different algorithms in the training set are shown in Figure 8.

In Figure 8, (a) shows the ability of each model on the behaviour metric MAE. MAE is one of the key indicators for model evaluation, which calculates the mean absolute deviation between predicted and actual values, and is used to characterize the count of network models. The smaller the value, the better the performance. From Figure 8 (a), the MAE value of the CNN-Transformer fusion counting algorithm was 10.13, which was the lowest compared to the other four counting algorithms. Figure 8 (b) shows the behaviour of each model on the performance metric RMSE. RMSE was another important indicator for model evaluation, which was the average square root error between the predicted and actual values. It was used to characterize the stability of network model counting, and the smaller its value, the better the stability of the model. The Transformer model had the highest value of 17.8. From Figure 8 (b), the RMSE value of the CNN-Transformer fusion counting algorithm was 12.08, which was the lowest compared to the other four counting algorithms. The RF model had the highest value of 16.7. The comparison results of MA and PSNR performance of different algorithms in the training set are shown in Figure 9.

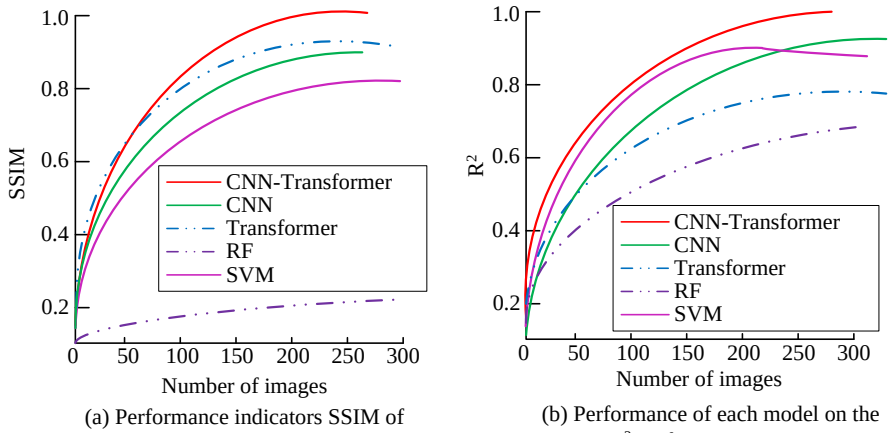
In Figure 9, (a) shows the behaviour of each model on the behaviour metric MA. The larger the MA, the higher the counting accuracy and stability of the network model. From Figure 9 (a), the MA value of the CNN-Transformer fusion counting algorithm was 98.6%, which was the highest compared to the other four counting algorithms. Figure 9 (b) shows the behaviour of each model on the behaviour metric PSNR. This indicator represents the quality of an image based on the error between corresponding pixels, so the higher the PSNR value, the higher the quality of the predicted generated image. In Figure 9 (b), the PSNR value of the CNN-Transformer fusion counting algorithm was the highest, at 23.75. Compared with the other four counting algorithms, this algorithm performed the best in image quality assessment. The comparison results of SSIM performance of different algorithms in the training set are shown in Figure 10.



(a) Performance indicators MA of each model

(b) Performance of each model on the PSNR performance metric

Figure 9: Performance of different algorithms on the MA and PSNR of the training set.



(a) Performance indicators SSIM of each model

(b) Performance of each model on the R^2 performance metric

Figure 10: Performance of different algorithms on SSIM and R2 in the training set.

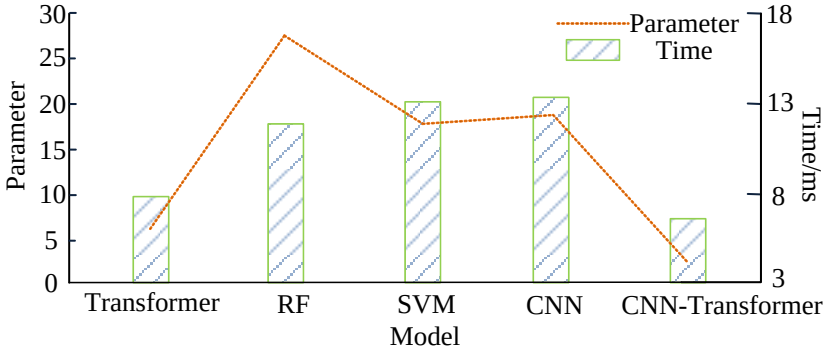


Figure 11: The counting time and parameter count of each algorithm model.

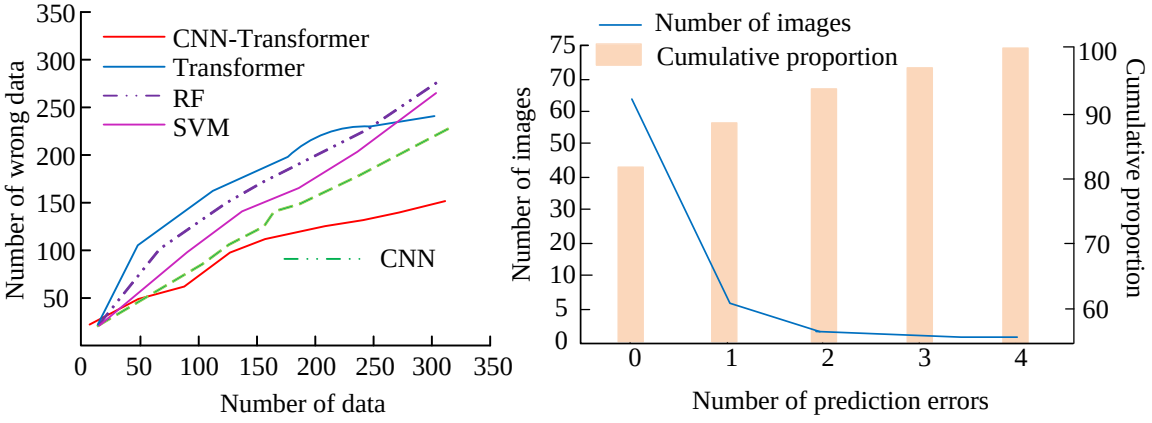
In Figure 10, (a) shows the specific situation of the training sets of five computer counting algorithms on SSIM. This indicator often considers the brightness, contrast, and structure of the image comprehensively to achieve the effect of measuring the correlation between pixels, making it closer to human subjective perception of image quality. Generally speaking, the closer the SSIM value is to 1, the higher the image quality predicted by the algorithm. From Figure 10, it is told that the SSIM value of the CNN-Transformer fusion counting algorithm was 0.933, which was closest to 1 compared to other models. In addition, compared with the other four algorithms, the convergence speed of the research algorithm was significantly higher in the SSIM image, with the convergence inflection point located around image number 40. Figure 10 (b) shows the specific situation of R2 for each model, which reflects the degree of fit of the model. From the figure, it is told that the R2 value of the CNN Transformer fusion counting algorithm was 0.901, which was closest to 1 compared to other models. Based on the above, the proposed counting algorithm that integrates CNN Transformer had good counting performance on the training set. Furthermore, to demonstrate the universality of the model application, the experiment also explored it on a publicly available dataset. This dataset is the Distribution Transformer Detection Dataset (DTD). The same performance indicators as mentioned above were selected for testing. The experimental results showed that MAE was 10.02, RMSE was 12.02, MA was 97.6%, PSNR was 23.55, SSIM was 0.934, and R2 was 0.911.

3.2 Testing and analysis based on CNN transformer counting algorithm model

In the above experiment, the proposed CNN-Transformer counting algorithm model performed well on the training set. To formalize more about the practical application ability of the model, the study intended to use a test set to analyze the model again. Among them, the study compared the recognition performance of various models by introducing the average detection time/ms and parameter quantity of a single image, as shown in Figure 11.

Figure 11 shows the specific situation of the five models in terms of time and parameters. The counting algorithm model that integrated CNN-Transformer had the shortest average counting time for a single image, about 6.58ms, and the smallest number of parameters, about 3.21. In comparison with the model with the longest average detection time for a single image, there was a difference of 6.62ms. Compared with the model corresponding to the maximum parameter count, there was a difference of 24.33. Obviously, the model proposed in the study had shorter recognition and counting time, and more efficient counting efficiency in actual counting. The above indicators reflected the overall testing performance of each model. To understand the situation of each model in counting error images, the study also tested the error counting probability of each model in the test set, recorded the image numbers of error counts in each counting algorithm, and summarized the number of times each image was counted incorrectly. The results are shown in Figure 12.

In Figure 12, (a) shows the false detection rates of different algorithms, and (b) shows the distribution of error count images. From Figure 12 (a), as the number of counting images increased, the error rates of each algorithm randomly increased. However, compared to the other four algorithms, the counting algorithm that integrated CNN-Transformer had a lower overall false detection rate. In Figure 12 (b), out of 76 test set images, 62 images were correctly counted by all models, accounting for 81.58% of the total; The number of images with an error count of less than or equal to 1 accounted for 88.15% of the entire test set. Among the five models mentioned above, there were a total of three images with a classification error rate higher than 50%. One of them was incorrectly counted by four models, indicating that this image had strong confusion and the category features might not be clear enough. The specific number of this image in the test set was 13, with 4 errors. The specific situation of the error probability of this image in the five models is represented in Table 3.



(a) False detection rates of different algorithms (b) Distribution of Error Counting Images

Figure 12: Error recognition status of each model.

Table 3: Probability of incorrect counting for figure 13 by each model.

Image number	Model	Predicted probability
13	CNN	[0.78,0.16]
	Transformer	[0.97,0.56]
	SVM	[0.93,0.64]
	RF	[0.92,0.18]
	CNN-Transformer	[0.59,0.51]

Table 3 shows the error count probabilities of each algorithm for high ambiguity image number 13. The true label of image 13 was a positive sample. From the figure, the intervals of the five counting algorithms in the two-dimensional vector were [0.77, 0.21], [0.96, 0.55], [0.92, 0.63], [0.91, 0.17], and [0.60, 0.30]. The first element in this interval was the probability of incorrectly judging a positive sample, and the second element was the probability of correctly judging a positive sample. Except for the CNN-Transformer model, all other models made incorrect judgments. Subsequently, after separate analysis, it was found that the high error rate of image number 13 was due to issues with lighting and occlusion. The CNN Transformer model combines the advantages of CNN and Transformer, using CNN to extract local features and Transformer to capture global contextual information, thus improving the model's ability to process blurry images. Overall, the counting algorithm that integrated CNN-Transformer still had good recognition and counting capabilities in high complexity scenarios.

4 Discussion

The fusion CNN-Transformer counting algorithm proposed in the study performed well in various performance analysis indicators of the training set data, with MAE of 10.13, RMSE of 12.08, MA of 98.6%, PSNR value of 23.75, and SSIM and coefficient of determination close to 1. In comparison with other algorithms, the algorithm raised in the study performed excellently in all indicators. In addition, in the test set, the experiment also compared the average single image counting time and parameter count of five counting algorithms. It was found that the CNN Transformer counting algorithm had the shortest average single image counting time of about 6.58ms, with a parameter count of 3.21 and the lowest quantity. In terms of error counting, all algorithms showed a trend where the more recognized images, the higher the false detection rate. However, for a single algorithm, the counting algorithm that integrated CNN-Transformer exhibited a lower overall false detection rate. In addition, in low feature and high ambiguity images, except for the counting algorithm that integrated CNN-Transformer, all other algorithms had incorrect recognition counts, indicating that the counting algorithm that integrated CNN and Transformer still had good counting ability in recognizing high complexity counting scenes.

The CNN Transformer model exhibited significant advantages in balancing the number of parameters, inference time, and model accuracy. In resource constrained environments such as farms and other practical application scenarios, traditional complex models often struggle to run stably due to the lack of powerful computing and storage capabilities of the devices in these scenarios. The research model, due to its limited number of parameters and fast inference speed, can adapt well to these resource constrained environments. Therefore, in practical applications, this model can accurately count the number of chickens and provide timely and accurate data support for farm managers. This helps them better understand the feeding situation, develop scientific feeding plans, and thus improve feeding efficiency and economic benefits. Meanwhile, due to the fast inference speed of the model, it can also meet the real-time requirements and provide real-time data feedback for farm managers.

In the same type of research, Zhang L et al. proposed a shrimp automatic local image-based enumerating way

utilizing lightweight YOLOv4, and constructed a local shrimp enumerating model grounded on Light-YOLOv4. The strategy underwent testing on a shrimp dataset, and the results showed that the Light-YOLOv4 local shrimp enumerating model acquired a enumerating accuracy of 92.12%, a recall rate of 94.21%, an F1 value of 93.15%, and an average accuracy mean of 93.16% [19]. Although the comprehensive counting ability of this model was superior, its average accuracy was lower than that of the model in this study. Wu Fy et al. fused the CNN Deeplab V3+model with traditional image processing algorithms and applied it to the detection and counting of banana bunches. The results showed that the final bundle perception precision was 86%, the accuracy of bacterial colony detection during harvesting was 76%, and the overall bacterial colony counting accuracy was 93.2% [20]. The results of this model were lower than the comprehensive behaviour of the model in this study.

The results of this study have significant advantages over existing technology, which may be attributed to the ability of CNN to handle local features and the modeling of global dependencies by Transformer. CNN can effectively extract local features of images, while Transformer captures global dependencies in images through its self attention mechanism. The combination of the two enables more accurate counting when dealing with complex scenes. However, this fusion also brings certain complexity, such as an increase in the number of parameters. However, this research model achieved fast inference time while maintaining a low number of parameters, indicating a good balance between complexity and efficiency.

5 Conclusion

Traditional counting relies on manual operation, with low processing power and efficiency, and often requires a lot of manpower and time to identify large-scale data. However, with the prosperity of Internet technique, computer vision technique can effectively solve this problem for object detection and counting. CNN and Transformer are representative models of deep learning. The former has good local FE ability, while the latter has a non cyclic structure based on attention mechanism and processes the entire input sequence in parallel. Based on this, the study integrated CNN with Transformer to construct a CNN-Transformer model, and explored its performance in target counting through simulation training and testing. The results showed that the model performed well in performance analysis. In testing analysis, the counting time and parameter count of the model were significantly lower than other models of the same type. However, it still performed well in low feature and high confusion image counting recognition. Although the research achieved good results, there were still some limitations, such as the lack of clear input-output mapping in the Transformer model compared to other models, which increased the difficulty of internal interpretation. In the future, efforts can be made to incorporate interpretable artificial intelligence technologies such as attention visualization or salinity maps to enhance the interpretability of models. In addition, the chicken breeding image dataset used in the study still has insufficient quantity in the context of deep learning. In the future, data augmentation techniques such as rotation, scaling, cropping, and flipping can be further adopted to increase data diversity and help models learn more robust features, thereby improving their generality.

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Advanced Optimal Cross-Modal Fusion Mechanism for Audio-Video Based Artificial Emotion Recognition

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Keywords: multimodal fusion, cross-modal fusion, emotion recognition, artificial emotion intelligence, fusion mechanism

Received: October 22, 2024

The advanced technology of artificial emotional intelligence has greatly contributed to multimodal emption recognition task. Emotion recognition has played a crucial role in many domains, like communication, e-learning, mental healthcare, contextual awareness, and customer satisfaction. As real-time data continues to expand, addressing the problem of emotion recognition has become critical and complex. A key challenge lies in recognizing emotions from multimodal heterogeneous input sources, aligning extracted features, and developing robust emotion recognition models. In this study, we explore a cross-modal (audio and video modality) fusion mechanism for emotion recognition, effectively addressing the associated feature complexities. We have used 2D-CNN and 3D-CNN deep learning models for audio and video feature extractions and developed robust models for emotion recognition. This study emphasizes the importance of Compact Bilinear Gated Pooling (CBGP) cross-modal fusion mechanism and highlights the contribution of fusing the features from audio and video modalities for emotion recognition. It also discusses the working principle and comparison performance with other peer cross-modal fusion techniques such as FBP and CBP. The performance of advanced cross-modal fusion is compared to baseline traditional cross-modal fusion mechanisms including EF-LSTM, LF-LSTM, Graph-MFN, hybrid fusion and transformer model based fusion mechanisms such as, attention fusion and transformer fusion. This experiment is performed on benchmark datasets CMU-MOSEI and achieves an accuracy of 80.3%, F1-score of 79.2%, and MAE of 54.2%.

Povzetek: Predstavljen je napredni mehanizem optimalne fuzije med modalnostmi za umetno prepoznavanje čustev na podlagi avdio-video posnetkov. Študija uporablja 2D- in 3D-CNN za ekstrakcijo značilnosti, poudarja pomen CBGP fuzije in dosega odlične razultate na naboru podatkov CMU-MOSEI.

1 Introduction

Emotion recognition is being successfully used in many domains and applications. The adoption of this technology has grown rapidly in healthcare, e-learning and advertising [1]. Initially, emotion recognition was limited to with unimodal approaches, but it has now gained more popularity with the advancement of multimodal approaches and enhanced techniques. Its growing demand has expanded the scope for exploring various directions of research in emotion recognition. Multimodal data inherently contains rich information and has the potential to learn meaningful patterns from extracted features. In our study, we intend to achieve emotion recognition by combining features extracted from audio and video modalities and employing a fusion mechanism. This study explores the cross-modal fusion approach, where the term 'cross modal fusion' refers to integrating essential features from heterogeneous input sources, further this integration helps in training deep learning models and classifying emotions effectively. Advanced cross-modal fusion mechanisms are categorized in three types: Factorized bilinear pooling (FBP) [2], Compact bilinear pooling (CBP) [3], and Compact Bilinear Gated Pooling (CBGP) [4].

Emotion recognition from audio and video modalities are very crucial because audio and video (collection of image frames) gives a wide range of information regarding, pitch, tone, image texture, facial movements, and facial expressions [5]. To train a model it is easy to extract features within the same modality and from another modality. This type of feature extraction leads to training a deep learning model to fine grained emotion classification tasks [6]. To work with different modalities, the most important and primary step is to extract the features from both the modalities. After preprocessing and cleaning the features, it is required to align those features, and combine only those features which have essential information and can help to train a deep learning model [7]. This study uses two different deep learning models, one is 2D-CNN [8] for audio modality and other is 3D-CNN [9] for video modality. As per the previous studies, this study aims to explore the advanced fusion mechanism such as Factorized bilinear pooling (FBP), Compact bilinear pooling (CBP), and Compact Bilinear Gated Pooling (CBGP). This study compares the

advanced fusion approaches with state-of-the-art fusion approaches such as early fusion, late fusion, and hybrid fusion, as well as transformer model based fusion techniques such as attention fusion and transformer fusion.

The research contribution of the proposed work are as follows:

- Highlights the limitations of traditional fusion mechanisms, such as high dimensionality, suboptimal interdependency modeling, and challenges in fine-grained emotion classification.
- Addresses a critical gap to reduce the computational errors and improve the sustainability of audio-video emotion recognition systems.
- Introduces a novel gating unit and cross-modal fusion approach using factorized bilinear pooling and compact bilinear pooling, addressing the inefficiencies in traditional fusion methods. This solution enhances feature interaction and reduces computational complexity.
- Employs lightweight 2D-CNN and 3D-CNN architectures for audio and video modalities, respectively, avoiding the need for pruning and quantization while maintaining network simplicity.
- This design minimizes computational overhead associated with insignificant weights and neurons. Validates the model's accuracy and compares the performance of all three advanced cross-modal fusion mechanisms using the benchmark dataset CMU-MOSEI.
- Validates the model's accuracy and compares the performance with baseline, and traditional state-of-the-art fusion approaches: early fusion, late fusion and hybrid fusion.
- Comprehensive discussion with transformer model based fusion approaches: attention fusion and transformer fusion.
- The proposed approach ensures scalability and sustainability, contributing to the development of more resource-efficient deep learning models for real-world applications.

The rest of the paper is organized as follows: section 2 reviews the literature on feature extraction and traditional fusion mechanism and highlights the related work and research gap. Section 3 introduces the advanced cross-modal fusion approaches. Section 4 presents the training model and experimental setup, section 5 provides the result and discussion, and finally, Section 6 concludes the paper and suggests future scope.

2 Literature review

This section offers an overview of the features of audio-video modalities, and the existing fusion mechanisms in multimodal emotion recognition, along with a detailed review. Table 1 summarizes the related work and some baseline cross-modal fusion mechanisms, particularly for emotion recognition in audio-video modalities using the CMU-MOSEI dataset.

2.1 Feature extraction

Before feature extraction, the raw input dataset is pre-processed to ensure it is free from noise, missing values and other inconsistencies [10]. Feature extraction is a crucial part of feature engineering in any classification model, which yields critical information from the input data. Feature sets act as input vectors for a deep learning model, containing all the necessary information about the modalities that help the model learn patterns [11]. This section reviews the features and feature sets of audio and video modalities utilized in previous research studies.

i. Audio features

To effectively train deep learning models with audio features, feature extraction tools and libraries such as LibROSA [12], OpenSMILE [13], and pyAudioAnalysis [14] has proven indispensable. These tools are essential to process and extract the meaningful features, offering a robust foundation for building a deep learning model. The process begins with raw audio data undergoing a preprocessing step. After preprocessing, audio features are extracted using these tools and libraries. These features contain the information about acoustic properties [15] of audio utterances embedded within the video track. The extracted feature provides crucial information about various feature segments such as pitch, tone, energy, rhythm, and spectral attributes [16]. These properties capture many useful insights from raw audio data to train the deep learning model, which drives to classify the emotional state. Some most widely used extracted key features include:

- Mel-Frequency Cepstral Coefficients (MFCCs) [17]: Derived from spectrograms to represent the audio signal in a form humans perceive.
- Spectral features [18]: Attributes such as spectral centroid, roll-off, bandwidth that highlight energy distribution across frequencies.
- Variations in pitch, frequencies, amplitude [19]: Capturing changes in voice that are indicative of different emotions.
- Energy and intensity levels [19]: it represents the changes in signal strength, where low intensity often refers to 'sad' and high intensity correlates with 'excitement or happy' emotions.

Video features

Extracting video features is an essential step to train a deep learning model for emotion recognition. This process takes multiple sub-steps like extracting frames from the video, setting the frames per second, and extracting per frame features. After extracting frames, it is required to preprocess the entire frames as per standards for emotion recognition.

This preprocessing includes tasks such as frame sampling [20], facial feature alignment [21], discarding irrelevant frames and reducing variations.

Previous studies have explored two broad approaches to extracting the features from frames: appearance-based features and geometric-based features [22].

Appearance-based features: These features describe the visual characteristics as features of a picture within a specific frame, such as the face, facial expression, expression textures, sharpness, and facial movements [23]. These features provide pure cues and essential information for recognizing emotions.
Geometric-based features: These features are determined based on the calculation of facial landmarks, jaw movements, eyebrow movements, expression coordinates, relative positions, distance, arcs, shape angles, texture angles, and other facial action parameters [24].

These features are extracted using machine learning algorithms [25]–[28], traditional feature extraction techniques [29]–[32], and currently deep neural network models [12], [33]–[35]. Python libraries and frameworks are now widely used for feature extraction processes, enabling the development of more robust models for emotion recognition.

2.2 Feature fusion mechanism

After extracting features from both the audio and video modalities, an integration process is required to combine them effectively. This process, known as information fusion or feature fusion, involves aligning the key features from each modality obtained during the feature extraction and fusing them into a unified representation [36]. The goal is to synchronize the features of both modalities to collaboratively recognize emotions with higher accuracy. In this fusion process, the integrated features are first used to train a deep learning model. The model is then validated to ensure its accuracy and reliability in emotion recognition.

Early fusion

Early fusion [5] is one of the simplest and most fundamental mechanisms for multimodal fusion. In this fusion mechanism, features from different modalities are first aligned and integrated after extraction and then fed into a deep neural network model as input. This method combines audio and features into a single unifies feature vector, by applying the concatenation or elementwise operations such as addition, multiplication the, processed by a deep learning classification model for emotion recognition.

Late fusion

To address the limitations of early fusion, another basic fusion mechanism, late fusion [37], was introduced. A significant amount of research has shifted towards this fusion mechanism to develop more robust emotion classification models. In late fusion, each modality is first pre-processed, analyzed, and fed into a deep neural network model as input. The outputs from these classification models are then combined at a later stage. The advantage of this fusion mechanism lies in its ability to fuse features with low dimensionality and accurately classify emotions.

Hybrid fusion

Hybrid fusion [38] is hybridization of early and late fusion, integrating the feature properties of both fusion principles. It is considered superior to early and hybrid fusion in emotion classification. This fusion is particularly useful for addressing the challenges associated with the complexity of early and late fusion. Hybrid fusion can be applied in two phases; first, during the initial feature interaction, and second, after the model has been trained. However, this fusion technique fails to manage large parameters and complex features, where extracting and combining correlation based spatiotemporal feature information and identifying patterns are critical in multimodal emotion recognition. Hence, hybrid fusion needs further improvements to deal with complex multimodal datasets.

Attention fusion

Attention fusion [39] is a mechanism that focuses on fusing only the most relevant and crucial features after extracting all the features and generating feature maps from multimodal inputs. The advantage of this approach is to excel in handling both inter-modality and intra-modality interactions effectively. However, a major drawback of this fusion mechanism arises when feature alignment errors occur in spatiotemporal datasets or when sequence synchronization is lacking. Such issues lead to weak attention scores, increasing data complexity and computational burden [40]. There are two types of attention fusion mechanisms: self-attention [41] and multi-head attention [13]. Self-attention fusion sequentially captures interactions within a single modality, while multi-head attention focuses on every aspect of feature representation and captures interactions as output from multiple heads in parallel.

Transformer fusion

Transformer fusion [42] is an advanced approach of fusion mechanism that leverages pre-trained transformer models, which scales well on long sequencing data due to their ability to perform parallel

computations. This fusion approach is particularly suitable for text-based emotion recognition tasks and natural language processing (NLP) applications, as it processes all token embeddings simultaneously. However, transformer fusion is less efficient when applied with audio and video modalities together. This limitation arises from the tokenization-synchronization trade-off between audio and video frame intervals, and positional embedding segments can lead to a loss of critical information and feature correlations in these modalities. Furthermore, the process results in imbalanced classification, complex computations, and high memory usage, making it less ideal for fusing spatiotemporal features and datasets.

Table 1: Summary of audio-video based traditional fusion and other fusion's related work.

Fusion	Feature extraction model	Modality	Datasets	Remarks
Early fusion [43]	LSTM	Audio-video	CMU-MOSEI	Sensitive to noise and misalignment between audio and video signals
Late fusion [43]	LSTM	Audio-video	CMU-MOSEI	High computational cost; less effective in modeling complex interactions between modalities
Hybrid fusion [44]	VGG-net	Audio-video	IIT-R SIER	Increased model complexity; risk of overfitting with limited data
Multimodal Factorization Model (MFM) [43]	Bayesian network	Audio-video	CMU-MOSEI	Computationally expensive; less scalable for large datasets
Graph-MFN (G-MFN) [45]	LSTM	Audio-video	CMU-MOSEI	Limited scalability
Multiplicative fusion (M3ER) [46]	LSTM	Audio-video	IEMOCAP, CMU-MOSEI	Prone to overfitting
Cross-Attention fusion [39]	Attention & concatenation	Audio-video	RAVDESS	Requires large amounts of data for effective attention training; sensitive to missing modality information
Transformer fusion [42]	Transformer-based pre-trained model	Audio-video	MELD, IEMOCAP, CMU-MOSEI	High memory consumption; needs extensive pretraining and large datasets
Multimodal fusion [47]	CNN	Audio-video	AVEC2017	Limited ability to capture temporal relationships;
Model level fusion [48]	2-layer LSTM	Audio-video	RECOLA	fine-tuning requires careful parameter tuning.
Tensor fusion network TFN [49]	Three-fold Cartesian product	Audio-video	CMU-MOSEI	Tensor-based fusion can be computationally prohibitive; sensitive to missing or noisy data.
Multimodal Dynamic Fusion Network [50]	Bi-directional gated recurrent unit (BiGRU)	Audio-video	IEMOCAP, MELD	Complex training process; BiGRUs can suffer from vanishing gradient problems with long sequences.

2.3 Research gap

Problem: Through a comprehensive review of the literature, we have gained crucial insights into audio and video feature extraction, various traditional cross-modal feature fusions (such as early, late hybrid, attention, and transformer fusion), and deep learning models, along with their comparative performances on benchmark multimodal datasets. Traditional fusion faces challenges with high dimensionality in large datasets, fails to optimize the interdependencies of features, and struggles with fine-grained emotion classification. However, a critical research gap still needs to be addressed to improve further, specifically to reduce the computational error in traditional fusion mechanisms for audio-video based emotion recognition systems and enhance their sustainability.

Solution: To address this gap, we propose a gating unit, and advanced cross-modal fusion mechanism (factorized

bilinear pooling and compact bilinear pooling) as an alternative to traditional methods. This approach employs 2D CNN and 3D CNN simple deep neural network architectures to avoid pruning and quantizing the mode while managing insignificant weights and neurons. This solution can optimize the computational efficiency while maintaining high performance, contributing to the development of more sustainable and scalable emotion recognition systems.

3 Material and methods

In this section, we first describe the cross-modal fusion mechanism and its architecture. Next, we introduce three advanced cross-modal fusion mechanisms and its algorithm to enhance audio-video based emotion recognition from audio and video modality. Finally, we discuss the comparative performance of these techniques against state-of-the-art fusion mechanisms.

3.1 Cross-modal fusion mechanism

Cross-modal fusion is an effective technique for emotion recognition that involves extracting meaningful and essential features from two or more heterogeneous input sources or modalities using feature extraction processes, integrating these features, and subsequently training a deep learning model. This technique has contributed to many applications including emotion recognition and has continually evolved, demonstrating its versatility and effectiveness. Notably, cross-modal fusion has been successfully applied in many applications such as object detection [51], night pedestrian detection [52] , low light image semantic segmentation [53], and depression detection [54]. Cross-modal fusion mechanism intends to develop a joint representation that gathers all the collective essential features from all the modalities and feeds into a single vector while retaining each modality's contributions.

While traditional cross-modal fusion mechanisms are discussed in the literature review section, this section focuses on three advanced cross-modal fusion mechanisms for emotion recognition: Factorized bilinear pooling (FBP), Compact bilinear pooling (CBP), and Compact Bilinear Gated Pooling (CBGP).

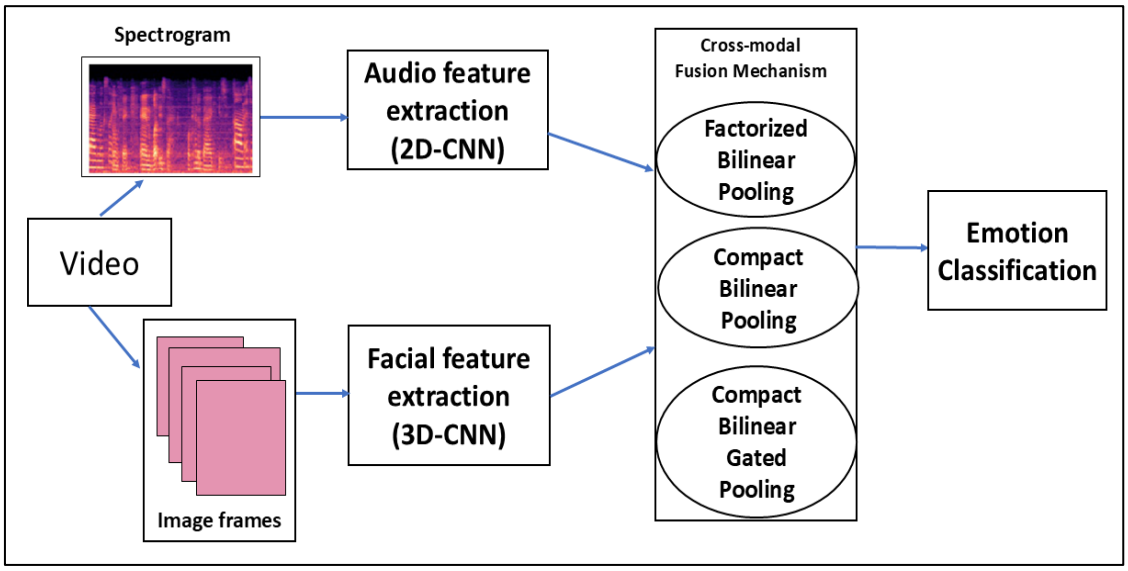

Figure 1: Basic architecture of Audio-video based cross-modal fusion mechanism

3.2 Factorized bilinear pooling (FBP)

Factorized Bilinear Pooling (FBP) is a method that enhances the standard bilinear pooling technique by factorizing the bilinear interaction tensor into lower-rank approximations [55]. Traditional bilinear pooling involves computing the outer product of two feature vectors from different modalities, resulting in a high-dimensional feature representation. While this method captures rich interactions between the modalities, it is computationally expensive and prone to overfitting due to the large number of parameters. FBP mitigates these issues by factorizing the interaction tensor into a product of two lower-rank matrices, significantly reducing the number of parameters while preserving the expressive power of bilinear interactions.

$$Z = \sum_{i=1}^{m} (M^T A) \,.\, (N^T V) \quad (1)$$

Where, Z: Pooled feature vector, M and N are bilinear interaction matrices, A and V are feature vectors from audio and video, respectively. Algorithm 1 illustrates the step-by-step factorized bilinear pooling fusion process implementation.

Training method: Let A' represents the Audio and V' represents the Video modality. The feature extraction functions f_a *and* f_v are applied to the audio and video modality. It generates the feature vectors:

$$F_A = f_a(A') \text{ and } F_V = f_v(V') \quad (2)$$

Where F_A *and* F_V are the extracted feature vectors from audio and video, D_A *and* D_V are dimensionality spaces of the audio and video feature spaces.

If the features from audio and video need to be combined, a fusion mechanism Σ can be used to integrate these feature vectors into a unified representation F'. It can be calculated as:

$$F' = \Sigma(F_A, F_V) \ \ or \ F = F_A \oplus F_V \qquad (3)$$

Algorithm 1: Factorized Bilinear Pooling (FBP)

Input: Factorize audio features: $F_A = f_a(A')$

Factorize video features: $F_V = f_v(V')$

Output: Predict the emotion class for new inputs

1. Compute the bilinear interaction between the factorized audio and video features: $F' = \Sigma(F_A, F_V) \ \ or \ F = F_A \oplus F_V$
2. Feed the compact bilinear pooled vector Z_{FBP} into a deep neural network classifier: $(F^i y^i)_{i=1}^N$
3. Calculate the loss function, minimize, and evaluation metrics
4. Use the trained model to predict the emotion class for new inputs.

This factorization reduces the computational burden and allows the model to generalize better, especially when dealing with limited data. FBP has been successfully applied in tasks such as Visual Question Answering (VQA) and image-text matching, where the interaction between modalities is crucial.

3.3 Compact bilinear pooling (CBP)

Compact Bilinear Pooling (CBP) further refines the bilinear pooling approach by employing compact representations of the bilinear interactions. Unlike standard bilinear pooling, which directly computes the outer product of two feature vectors, CBP leverages approximations based on the Tensor Sketch technique to produce a compact representation of the outer product. This method dramatically reduces the dimensionality of the resulting feature vector without losing the key interactions between modalities. Algorithm 2 illustrates the compact bilinear pooling fusion process implementation.

In CBP, the outer product of the feature vectors A and V is approximated by projecting both vectors into a higher-dimensional space using random projections, followed by element-wise multiplication and summation. Presented equation represents how to implement CBP for audio-video emotion recognition using a deep neural network:

$$Z = \sum_{i=1}^{m} (proj_a(A)_i) \,.\, (proj_v(V_i)) \qquad (5)$$

A prediction function f (F') is then applied to the feature vector F' to predict the target emotion category value, Z' so, $Z' = f(F)$. Here, $f(F)$ is a 2D-CNN deep neural network acting as a classifier. The model is trained on labelled dataset so it is calculated as follows:

$$(F^i y^i)_{i=1}^N \qquad (4)$$ Where y^i is the true prediction label and N is the size of the sample.

Where, Z: Pooled feature vector, A and V are feature vectors from audio and video, respectively. $proj_a$, and $proj_v$ are projection matrix of audio and video features.

Training Method: Let A' represents the Audio and V' represents the Video modality. The feature extraction functions f_a *and* f_v are applied to the audio and video modality. It generates the feature vectors:

$$F_A = f_a(A') \ and \ F_V = f_v(V') \qquad (6)$$

CBP uses random projections to project the high-dimensional feature vectors into a lower-dimensional space before combining them. Random projection for audio (Z_A) and video features (Z_V):

$$Z_A = (P_A F_A) \ \text{ and } \ Z_V = (P_V F_V) \qquad (7)$$

Where, $Z_{A/V}$: Projection of audio /video, P_A, and P_v: Projection matrix of audio /video features. To maintain the information during projection, random sign vectors are applied to the projected features.

$$ZA' = SA \circ ZA \text{ and } ZV' = SV \circ ZV \qquad (8)$$

SA and SV are random sign vectors for audio and video features, $\circ$ *denotes element wise multiplication.* Then we applied the random permutation to the elements of the signed vectors to further scramble the features.

$$Z_{A"} = Permute(Z'_A, h_A), \ and \ Z_{V"} = Permute(Z'_V, h_V) \qquad (9)$$

where, h_A, h_V is a permutation vector applied to the indices of Z'_A and Z'_V.

The core of CBP involves computing the circular convolution of the two permuted feature vectors:

$$Z_{CBP} = FFT^{-1}\left(FFT(Z_A)\right) \circ \left(FFT(Z_V)\right) \qquad (10)$$

FFT^{-1} : $inverse\ fast\ fourier\ transform$, and

FFT: $fast\ fourier\ transform$

After this we normalized the obtained CBP feature vector and classified the categories of emotions by using deep neural networks. Calculated with the following formula:

$$Z'_{CBP} = softmax(Z_{CBP}) \quad (11)$$

where Z'_{CBP} predicts the emotion class, and $softmax(Z_{CBP})$ represents the function of the deep neural network.

Algorithm 2: Compact Bilinear Pooling (CBP)

Input: Project audio features, Z_A *and*

Project video features, Z_V

Output: Predict the emotion class for new inputs

1. Generate projection matrix, ZA'
2. Apply sign vectors to the projected audio features $ZA' = SA \circ ZA$
3. Apply sign vectors to the projected video features $ZV' = SV \circ ZV$
4. Apply permutation to the audio features: $Z_{A''} = Permute(Z'_A, h_A)$
5. Apply permutation to the video features: $Z_{V''} = Permute(Z'_V, h_V)$
6. Compute the circular convolution of the two permuted feature vectors: $Z_{CBP} = FFT^{-1}\left(FFT(Z_A)\right) \circ \left(FFT(Z_V)\right)$
7. Feed the compact bilinear pooled vector Z_{CBP} into a deep neural network classifier: $Z'_{CBP} = softmax(Z_{CBP})$
8. Calculate the loss function, minimize, and evaluation metrics
9. Use the trained model to predict the emotion class for new inputs.

3.4 Compact bilinear gated pooling (CBGP*)*

Compact Bilinear Gated Pooling (CBGP) enhances and builds upon Compact Bilinear Pooling (CBP) by adding a gating mechanism that adjusts or selectively emphasizes features based on their relevance, using a learned Softmax function to modulate feature interactions before pooling.

In CBGP, the feature vectors A and V undergo compact bilinear pooling as described in CBP, but before the final summation, the resulting interaction vector is element-wise multiplied by a gating vector $G' \in R^d$ Where, d is the dimensionality of the compact representation. The gating vector is computed as:

$$G' = \sigma(W_G(A', V') + b_G) \quad (12)$$

Where σ: $softmax\ function$, W_G : weight matrix, b_G: bias vector, A', V': audio, video feature vectors.

Training Method: Let A' represents the Audio and V' represents the Video modality. The feature extraction functions $f_a\ and\ f_v$ are applied to the audio and video modality. It generates the feature vectors:

$$F_A = f_a(A') \text{ and } F_v = f_v(V') \quad (13)$$

CBP uses random projections to project the high-dimensional feature vectors into a lower-dimensional space before combining them and calculates the random projection for audio (Z_A) and video features (Z_V):

$$Z_A = P_A F_A \ \ and \ \ Z_V = P_V F_V \quad (14)$$

Where $Z_A\ and\ Z_V$: Projection of audio and video, P_A, and P_v: Projection matrix of audio and video features. Then, we compute element-wise multiplication of the projected vectors:

$$Z' = Z_A \circ Z_V \quad (15)$$

Gated pooling: (i) compute the introduced gating vector $G' \in R^d$ Where, d is the dimensionality of the compact representation. The gating vector is computed as:

$$G' = \sigma(W_G(A', V') + b_G) \quad (16)$$

Here, σ is a Softmax function.

(ii) then we apply the gating mechanism to the element-wise multiply vector:

$$Z'' = G' \circ Z' \quad (17)$$

Finally, we sum the elements of the gated interaction vector to obtain the final pooled vector by the following equation-

$$Z = Sum(Z'') \quad (18)$$

This entire mechanism can be summarized by an equation, Where, Z: pooled feature vector, Z_A,$and\ Z_V$: Projection of audio and video.

$$Z = \sum_{i=1}^{m} \left(\sigma(W_G\ (A, V) + b_G)\right)_i . (Z_A)_i) . (Z_V(V_i)) \quad (19)$$

Algorithm 3: Compact Bilinear Gated Pooling (CBGP)

Input: Project audio features: Z_A, and Project video features: Z_V

Output: Predict the emotion class for new inputs.

1. Compute gating vectors for audio and video features: $G' = \sigma(W_G(A', V') + b_G)$

2. Apply the gating vectors to the projected features: $$Z' = Z_A \circ Z_V$$
3. Apply sign vectors to the gated audio features: $$ZA' = SA \circ ZA$$
4. Apply sign vectors to the gated video features: $$ZV' = SV \circ ZV$$
5. Apply permutation to the gated and signed audio features: $$Z_{CBGP} = FFT^{-1}\,(P(FFT(Z_A \cdot G)))$$
6. Apply permutation to the gated and signed video features: $$Z_{CBGP} = FFT^{-1}\,(P(FFT(Z_V \cdot G)))$$
7. Compute the circular convolution of the two permuted feature vectors: $$Z'' = G' \circ Z'$$
8. Normalize the pooled feature vector: $$Z = Sum(Z'')$$
9. Feed the compact bilinear gated pooled vector Z_{CBGP} into a deep neural network classifier: $$Z_{CBGP} = \sum_{i=1}^{m} (\sigma(W_G\,(A,V) + b_G))_i . (Z_A)_i) . (Z_V(V_i))$$
10. Calculate the loss function, minimize, and evaluation metrics
11. Use the trained model to predict the emotion class for new inputs

Through this mathematical analysis, CBGP has been able to identify the optimal fusion approaches that can be applied to audio-video-based emotion recognition systems, ultimately contributing to the development of more robust and accurate emotion recognition technologies. The gating mechanism allows to control the flow of information between the layers while selecting and rejecting the relevant or non-relevant (based on correlation feature score) inputs. As we know, not all the features are equally important at every step or time frame, so the gating mechanisms dynamically assign weights to features to capture complex regions more effectively.

4 Model training and experiments

Our experiments are conducted on a system equipped with an AMD Ryzen 7 processor, 16GB of RAM, and an NVIDIA GeForce RTX GPU. The code was implemented using Jupyter Notebook IDE and the PyTorch framework. For audio and video preprocessing, we utilized the Librosa and OpenCV Python libraries.

4.1 Evaluation dataset

CMU-MOSEI [37]**:** CMU-MOSEI dataset comprises over 23,259 annotated video clips collected from more than 1,000 speakers across a diverse range of topics. Total number of videos is 3228, video clips contain naturally occurring monologues in English, making the dataset a realistic representation of human communication. The dataset is annotated with six categorical emotions: happy, sad, angry, fear, disgusted, and surprised. Additionally, CMU-MOSEI provides intensity scores for each emotion, allowing for a fine-grained analysis of emotional expressions. After preprocessing, 20,323 samples are processed for feature extraction. The dataset is divided into three sets; 80% for training, 10% for testing, and 10% for validation. The performance is evaluated on Accuracy, F1-score, and mean absolute error, (MAE).

4.2 Deep learning model implementation details

a. 2D-CNN for Audio feature extraction and training model

We used 2D-cnn to extract and capture inter-modal feature dependencies from the CMU-MOSEI dataset. To generate spectrograms from raw audio files, we used the LibROSA library, which converts the raw audio waveform into a time series sampled at 22500 Hz. The waveform is then transformed into a spectrogram using the Short-Time Fourier Transform (STFT), with a window size of 2048 and a hop length of 512, striking a balance between time and frequency resolution. Spectrograms play a crucial role in audio-video emotion recognition as they align with video frames, increasing the likelihood of feature correlations due to time and frequency samples during fusion mechanism.

b. 3D-CNN for video feature extraction and training model

We used a simple 3D-CNN model because emotion recognition requires synchronized feature relations in each frame of a video, and a compact bilinear gated fusion mechanism can increase computational complexity. Additionally, our proposed approach aims to extract spatial and temporal features and incorporates a gated filter to fuse features from the audio and video modalities for each utterance. Therefore, we chose a simple deep learning architecture. The 3D-CNN takes a 224x224x3 image as input, which passes through the first 3D convolution layer followed by pooling layers, with a filter size of 3x3x3 and a stride of 1. Table 2 illustrates the Hyperparameters for 2D-CNN and 3D-CNN model.

Table 2. Hyperparameters for 2D-CNN and 3D-CNN model

Hyperparameter (2D-CNN) Audio	Hyperparameter (3D-CNN) Video
Input size= 224x224 Spectrogram	Input size=224x224x3 image frames
Kernels (conv layers) =32,64,128,256	Kernels (conv layers) = 64,128,256,512
Stride=1	Stride=1
Activation function= Relu and Softmax	Activation function= Relu and Softmax
Max Pooling= 2x2	Max Pooling= 3x3x3, 2x2x2
Batch size=32	Batch size=32
Epochs= 30	Epochs= 30-50
Learning rate=0.00003 (cosine decay)	Learning rate=0.00003 (cosine decay)
Regularization=L2	Regularization= L2
Dropout= 0.3%	Dropout=0.2%
Optimizer = Adam	Optimizer = Adam

5 Result and discussion

We evaluate the performance of each cross-modal fusion mechanism (FBP, CBP,CBGP) and compare it with the state-of-the-art (early fusion, late fusion and hybrid fusion) mechanisms on the CMU-MOSEI dataset using accuracy, F1-score, and MAE. F1-Score is the harmonic mean of precision and recall metrics. The results are summarized in the tables below, highlighting the contributions of each fusion method to the overall system performance

5.1 Ablation study

To investigate the specific contributions of compact bilinear gated pooling fusion (CBGP) of cross-modal fusion mechanism, this paper presents a detailed analysis of a series of ablation experiments conducted on the CMU-MOSEI datasets. These results are presented in tables, comparing key performance using accuracy, F1-score, and MAE among advanced cross-modal fusion mechanisms such as bilinear gated pooling, compact bilinear pooling, and compact bilinear gated pooling. We analyse the accuracy of each traditional fusion mechanism such as early fusion, late fusion and hybrid fusion on the same dataset, CMU-MOSEI. This approach employs 2D CNN and 3D CNN simple deep neural network architectures to avoid pruning and quantizing the mode while managing insignificant weights and neurons. The ablation study was carried out with a feature extraction process where features are audio and video modalities that interact through the outer product. The outer product allows the 2D-CNN and 3D-CNN to capture the interactions between every feature of one modality and every feature of the other modality in a compact manner. Comprehensive analysis and baseline comparisons show that our proposed CBGP fusion mechanism fuses feature effectively and outperforms the state-of-the-art fusion approaches. This study also provides a comprehensive discussion about transformer model based fusion approaches- attention fusion and transformer fusion.

5.2 Baseline comparisons

a. Comparison of advanced cross-modal fusion mechanism with state-of-the-art FBP, and CBP fusion mechanism.

Table 3: Performance comparison of advanced cross-modal fusion mechanisms on CMU- MOSEI dataset, highlighting their accuracy, F1-score, MAE, and specific strengths.

Cross-modal fusion mechanism	Accuracy (%)	F1-Score (%)	MAE	Remarks
FBP	76.9	75.6	59.1	Performs well with sentiment-emotion overlap
CBP	78.4	77.1	59.8	Captures diverse emotions effectively
CBGP	**80.3**	**79.2**	**54.2**	**Best for fine-grained emotion detection**

Table 3 illustrates that CBGP achieves the highest scores, particularly excelling in recognizing fine-grained emotions. Its ability to dynamically adjust the importance of different feature interactions allows it to handle the nuanced and varied expressions found in the illustrations in the CMU-MOSEI dataset.

b. Comparison of advanced cross-modal fusion mechanism with baseline cross-modal fusion mechanism

Table 4: Performance comparison of advanced cross-modal fusion mechanism with traditional, and baseline cross-modal fusion mechanism on CMU-MOSEI dataset, highlighting their accuracy, F1-score, and MAE.

Fusion Mechanism	Accuracy (%)	F1-score (%)	MAE (%)
Early fusion (EF-LSTM) [43]	78.2	77.9	64.2
Late fusion (LF-LSTM) [43]	80.6	80.6	61.9
Graph-MFN [45]	76.9	77.0	-
HFU-BERT model [56]	73.2	72.0	86.7
Early Fusion 2D-CNN (Ours)	67.3	65.4	69.7
Late Fusion 2D-CNN (Ours)	70.4	69.2	67.4
Hybrid Fusion 2D-CNN (Ours)	72.6	71.4	65.8
FBP (Ours)	76.9	75.6	59.1
CBP (Ours)	78.4	77.1	59.8
CBGP (Ours)	**81.3**	**79.2**	**54.2**

Table 4, illustrates that FBP performs well in scenarios involving sentiment-emotion overlap. CBP further improves by effectively capturing a diverse range of emotions. CBGP achieves the highest performance over traditional cross-modal fusion mechanisms due to limited feature interaction and correlation. CBGP excels in fine-grained emotion recognition and setting a benchmark on CMU-MOSEI dataset.

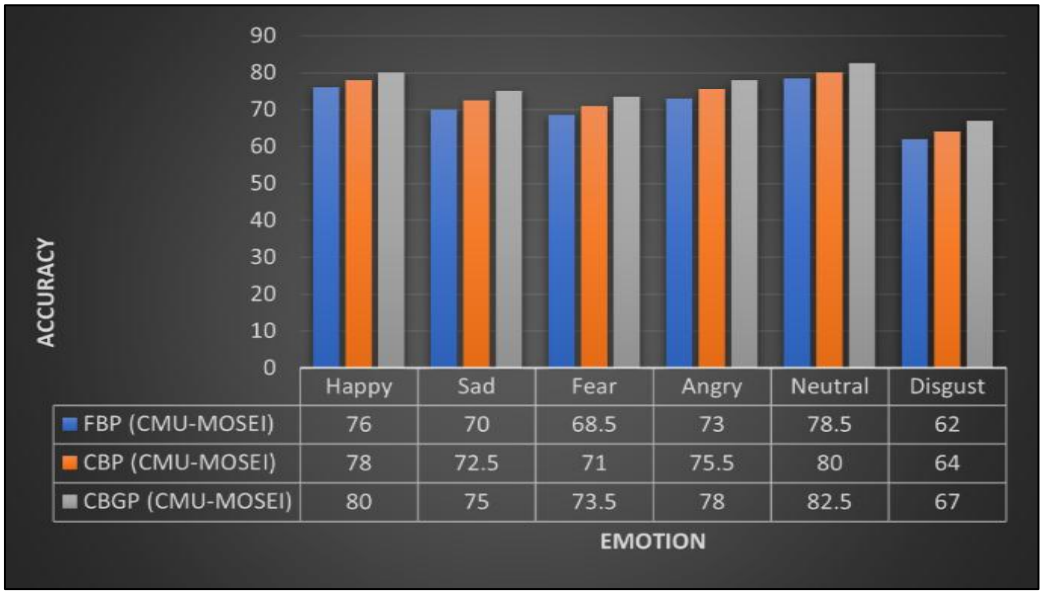

Figure 2: Accuracy performance of FBP, CBP, and CBGP fusion approaches on CMU-MOSEI

Figure 2 illustrates that in the CMU-MOSEI dataset emotion categories, CBP consistently outperforms FBP. The accuracy of 'Happy' emotion recognition increases from 76% (FBP) to 78% (CBP), and 'Sad' improves from 70% to 72.5%. CBGP provides higher accuracy than all other fusion mechanisms across all emotion categories. The progression from FBP to CBP, and from CBP to CBGP, emphasizes the strength and effectiveness of the fusion model in capturing emotional feature cues. This fusion leads to meaningful results that help classify emotion categories more accurately.

c. System complexity analysis

Table 5: Computational costs comparison (in floating point operations) for FBP, CBP, and CBGP approaches across CMU-MOSEI Datasets.

Datasets	FBP	CBP	CBGP
CMU-MOSEI	4.5×10^6	3.8×10^6	4.0×10^6

Table 5 presents the computational cost comparison, and highlights the relative efficiency of the FBP, CBP, and CBGP approaches on the CMU-MOSEI dataset. Despite the apparent efficiency of CBP, the marginal difference in computational costs, particularly the 0.2×10^6 FLOP gap between CBP and CBGP, raises questions about the trade-offs in performance. Lower computational costs may come at the expense of reduced accuracy or robustness in multimodal emotion recognition tasks. The slight increase in CBGP's computational load may reflect the additional overhead required to manage bi-modal interactions and graph-based modeling, potentially leading to enhanced performance and interpretability.

Table 6: Performance comparison of accuracy and p-value for cross-modal fusion mechanism.

Cross-modal fusion mechanism	Accuracy (%)	p-value
FBP	76.9	0.004
CBP	78.4	0.003
CBGP	**80.3**	**0.002**

Table 6 presents the accuracy and p-value of Full Bilinear Pooling (FBP), Compact Bilinear Pooling (CBP), and Compact Bilinear Gated Pooling (CBGP), where FBP achieves the lowest accuracy of 76.9%. CBP improves accuracy to 78.4% by introducing compact bilinear pooling. CBGP achieves the highest accuracy of 80.3% by incorporating the gating mechanism, which selectively emphasizes relevant features. The p-value decreases across the methods, indicating improved statistical significance with increasing accuracy. The values (0.004 for FBP, 0.003 for CBP, and 0.002 for CBGP) demonstrate that the performance improvements are statistically significant.

d. Comparison of CBGP fusion mechanism with attention fusion and transformer fusion

Transformer fusion: Transformer fusion is an advanced approach of fusion mechanism with the help of a pre-trained transformer model, which scales well to large datasets and long sequences due to parallel computations. This fusion is suitable for text-based emotion recognition tasks and natural language processing-based (NLP) applications because transformer fusion model such as BERT [57], RoBERTa [40] performs on all token embeddings parallelly which is not efficient to work with audio and video modalities together. Audio and video have large interdependencies of features and long sequences, as a result, the computational cost will be very high, training and testing will need more memory and computational burdens. Transformer fusion will also face challenges to extract, fuse and learn complex spatiotemporal features without architectural modifications in the model. Transformer fusion works by dividing the word sequences into tokens, which is feasible but if we divide long audio signals and high frame rate videos can lead to loss of important features, fine-grained temporal information, tokenization can reduce the effectiveness and increase the biases in SoftMax function.

Attention fusion: In our proposed work, we opted for CBGP over attention fusion to reduce the computational cost because the CMU-MOSEI dataset is largest dataset, and our proposed solution uses 2D-CNN for audio and 3D-CNN for video modalities to avoid pruning and quantizing the mode while managing insignificant weights and neurons. If we apply an attention fusion mechanism, we would need to apply self-attention fusion separately for both models and then integrate their outputs using multi-head attention fusion. This entire process would likely result in high dimensionality and an increased number of trainable parameters, leading to high memory usage and expensive computation.

Attention mechanism relies on element-wise scale dot products, which may cause high variance during training Since our implementation employs a simpler CNN architecture, in that case the model could predict unbalanced attention scores. The extreme parameters could further cause exponential computation issues, as unbalanced attention implies that the model may focus excessively on some regions while ignoring others. In conclusion, while attention fusion is an effective fusion mechanism, it is not a suitable fit for our employed deep learning emotion recognition model that's why we have excluded it from the experiment. It may perform better with architectures such as fit well in ResNet [12], DenseNet [58], MobileNet [59], and other transformer-based models, where its capabilities can be better utilized.

5.3 Why CBGP outperforms better?

Representation capacity

Traditional fusion: Traditional fusion typically concatenate or aggregate features from multiple modalities, which can result in linear combinations of features, whereas attention and transformer fusion enhance inter-modality interactions by learning feature weights, but they still rely on additive or multiplicative relationships between modalities. They often struggle with complex feature interactions and fail to capture higher-order dependencies effectively.

Advanced fusion: Factorized bilinear and compact bilinear pooling can capture non-linear and higher-order interactions between features across modalities, which allows richer representations. These methods compress the high-dimensional feature space into a lower-dimensional representation while preserving inter-modal relationships, addressing the curse of dimensionality in traditional bilinear pooling.

Computational efficiency

Traditional fusion: Simple concatenation or weighted aggregation methods are computationally inexpensive but may lead to redundant or over-complex representations. Transformer-based fusion, although effective, can be computationally expensive due to quadratic complexity in multi-head attention over long sequences or large modalities.

Advanced fusion: Compact bilinear pooling and gated pooling introduce compact representations by leveraging approximations (e.g., Random Fourier Transform or Count Sketch). These methods significantly reduce computational and memory overhead compared to traditional bilinear pooling without losing important interaction features.

Dimensionality reduction

Traditional fusion: These methods often rely on post-fusion dimensionality reduction techniques (e.g., PCA) to manage high-dimensional outputs. However, these approaches are not integrated into the fusion process, potentially leading to loss of modality-specific information.

Advanced fusion: Methods like compact bilinear and gated pooling perform dimensionality reduction implicitly during fusion, ensuring that only the most relevant and informative interactions are preserved.

Modality-specific challenges

Traditional Fusion: Early and late fusion assume modalities contribute equally, potentially underperforming in scenarios where modalities have asymmetric importance or varying quality. Transformers address some modality-specific issues but may fail in noisy or sparse input scenarios without sufficient modality-specific pretraining.

Advanced fusion: Compact bilinear and gated pooling are robust to modality-specific variations. For example: Gated pooling introduces selective weighting mechanisms that dynamically prioritize certain modalities or features based on their relevance. Factorized pooling ensures that noisy or less-relevant features are naturally down-weighted during fusion.

Generalization and scalability

Traditional fusion: Simple techniques like early and late fusion can generalize well but may not scale effectively to high-dimensional, multimodal, or diverse datasets. Transformer-based fusion can scale better but may require large datasets and pretraining to perform effectively.

Advanced fusion: Advanced techniques like compact bilinear pooling generalize well to high-dimensional data and work effectively on smaller datasets due to efficient feature compression. Factorized approaches reduce overfitting by limiting parameter count, improving scalability to complex multi-modal systems.

Interpretability

Traditional fusion: Approaches like attention fusion or transformer-based fusion are somewhat interpretable due to explicit weighting schemes or attention maps. However, early and hybrid fusion methods lack interpretability since features are often combined in a black-box manner.

Advanced fusion: Compact bilinear pooling and gated pooling methods often lack explicit interpretability because the transformations (e.g., random projections, Fourier transforms) are more abstract.

Table 7: Comparison of FBP, CBP and CBGP based on various parameters.

Cross-Modal Fusion	Feature interaction level	Feature map dimensionality	Computation cost	Advantage	Limitation
FBP	Element-wise product	Reduced $k \ll d^2$	Low	Efficient approximation of bilinear pooling	Introduces small approximation errors.
CBP	Tensor sketching	Compact $k \ll d^2$	Medium	Balances efficiency and expressiveness	It does not capture the full bilinear interactions
CBGP	Selective Second order interaction	Compact $k \ll d^2$	Medium	Best for fine-grained classification, emphasizes key features	Require extensive hyperparameter tuning.

Table 7 discusses the performance of FBP, CBP and CBGP based on various parameters such as, feature interaction level, feature map dimensionality, computational cost, advantage and limitation various parameters. Here, d^2 represents the input feature dimensionality, and k is the dimensionality of the output representation in bilinear pooling. In CBP and CBGP, the value of k is important as it directly affects the trade-off between computational efficiency and model expressiveness. If k is lower than small memory needed but model may lose some effectiveness. Conversely, if k is higher, the model acts more expressively but the computational cost increases.

5.4 Real-time application

As we have seen in the above sections, CBGP has proven to be an effective fusion mechanism over traditional fusion mechanisms. This comprehensive study has demonstrated its full capability as cross-modal based emotion recognition. In real-time application, CBGP can extend beyond audio and video fusion. It can contribute significantly in audio-video-text based real-time applications as well. CBGP is a computationally effective and robust fusion mechanism, making it crucial to capture high correlation and relevant features for fusing heterogeneous modalities. Here are some real-time applications where CBGP can be applied in, Computer vision and pattern recognition, Natural language Process based language interactions, Recommendation systems for customer, Healthcare and medical applications, Robotics and automation system, Banking and E-commerce based digital applications, Security and surveillance based human safety application.

6 Conclusion & future scope

This study investigates the effectiveness of three advanced cross model fusion mechanisms; factorized bilinear pooling, compact bilinear pooling, and compact bilinear gated pooling for audio-video based emotion recognition. This comprehensive experiment is

conducted on a widely recognized dataset; CMU-MOSEI. The gating mechanism integrated within CBGP enables the model to selectively emphasize relevant feature interactions, which is crucial for accurately recognizing complex and nuanced emotional expressions. We evaluated the performance of each fusion technique across various emotional categories, including happy, sad, fear, anger, neutral and disgust. The performance of advanced cross-modal fusion is compared to traditional cross-modal fusion mechanisms like early fusion, late fusion and hybrid fusion and transformer model based fusion mechanisms like, attention fusion and transformer fusion. The experimental results clearly demonstrate that the compact bilinear gated pooling (CBGP) mechanism outperforms the other fusion techniques across benchmark dataset, consistently achieving higher accuracy, F1-score, and MAE. Overall, the findings from this study suggest that incorporating a gating mechanism in multimodal fusion processes can significantly enhance the performance of emotion recognition systems, making CBGP a promising approach for future developments in this field.

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Deep Learning-Based Involution Feature Extraction for Human Posture Recognition in Martial Arts

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Keywords: human action recognition, deep learning, long- and short-term memory neural networks, lightweight networks, feature extraction

Received: August 30, 2024

With the development of computers in recent years, human body recognition technology has been vigorously developed and is widely used in motion analysis, video surveillance and other fields. This study is based on deep learning to improve human pose estimation. Firstly, Involution's feature extraction network was proposed for lightweight human pose estimation, and this feature extraction network was combined with existing human pose estimation models to recognize human pose. Label and classify each joint point of the human body separately, add weights to each different part, extract feature between joint points at different times, and then input the extracted feature into long short-term memory neural networks for recognition. The experimental results show that the improved human pose estimation model reduces the parameter and computational complexity by about 40% compared to the original model, while also slightly improving accuracy. Comparing the performance of models under various algorithms with the proposed model in this study, the accuracy under the Eigen method is 81.3%, the accuracy under the STOP method is 82.5%, the accuracy under the DMM&HOG method is 85.3%, the accuracy under the Actionlet method is 87.6%, and the accuracy under the JAS&HOG2 method is 83.5%. The accuracy of the InNet LSTM method is 90.6%. The results indicate that the proposed model has good performance and can recognize different martial arts movements.

Povzetek: Za prepoznavanje človeške drže v borilnih veščinah so porabljene involucijske ekstrakcije značilk za globoko učenje.

1 Introduction

With the development of computers, artificial intelligence has become increasingly relevant to people's lives. The advent of computer vision enables computers to automatically recognize human actions and classify them [1]. Initially human movement recognition relied on decomposing video frame by frame and then acquiring information from it, and then recognizing human movements through image processing. This approach requires manually designing motion feature to represent the human body and then modelling the motion feature to achieve the recognition effect, but manually acquiring the feature requires a lot of time and effort [2]. In this study, a human skeleton network was created by using Deep Residual Networks (ResNet) combined with Involution's improved algorithm for feature extraction. The human posture at each moment is represented by the human skeleton, so that the human posture feature can be quantified by the human skeleton network. The extracted feature is then fed into the Long Short-Term Memory (LSTM) neural network for processing and recognition. This model is designed to efficiently extract and accurately recognize and classify human feature. The research is divided into four main sections, the first of which is a brief review of other research topics on human recognition. The second part is a review of the main methods used in this research, and the third part is the results of the model obtained by applying the methods to the research and analysing the results. The fourth part is a summary of all the above studies and an outlook for future research.

2 Literature review

With the development of computers, human body recognition technology has been vigorously developed and is widely used in motion analysis, video surveillance, etc. Liu et al. proposed a method for estimating the 3D pose of a single person in two views without camera parameters in order to cope with the problem of needing to know the camera parameters to obtain coordinate accuracy in the camera's two views. It extracts the joint points from two different views through 2D estimation and inputs them into a 3D regression network to generate 3D joint point coordinates. The coordinates are then combined with a 3D human pose recognition model to identify the human pose. The results of the study

indicated that this method extracted a high accuracy rate for human pose action recognition [3]. Ferreira et al. proposed a skeleton structure and deep semantic feature based on human pose estimation network to train a repetition counting and validation system, which is able to make detection of human activities and quickly identify the function of invalid repetition information. The results show that the system is able to accurately identify human movements and remove invalid repetitive information from them [4]. Liu et al. propose a new elliptical distribution coding method in order to help computers to accurately identify human movements. The method first describes the human skeleton by elliptical Gaussian coordinate coding, then measures the difference between the predicted heat map and the ground truth heat map, and finally the human pose images for recognition. The results of the study show that the method has a good performance in both datasets of the experiment and can provide high recognition accuracy [5]. Vishwakarma proposes a method for recognizing human actions in videos that can be identified by deterministic actions, which uses a double transform of wavelets to perform feature extraction of human actions. The extracted feature is then recognized. The results show that the method has high recognition accuracy in different datasets [6]. Tian et al. argue that the key points of the human body under many images in the video may produce unreasonable prediction results from the human pose estimation method due to issues such as illumination, occlusion, etc. To address this problem, the team designed a new generative adversarial network to address the situation where some keypoints are not visible, but the model still has high recognition accuracy. The model consists of two components, namely a cascaded feature network and a graph structure network. The results show that the model has excellent recognition accuracy [7]. Zhang et al. found that existing 3D human pose estimation methods focus on overall joint error reduction, which leads to large errors in endpoint and bone length. To address this problem, the group proposed a human structure-aware network that can extract feature data from existing 2D joints to repair the positions of 3D joint points. The results show that this method can effectively reduce the error between endpoint and bone length, resulting in a high improvement in recognition accuracy [8].

Ht et al. found that traditional human action recognition uses manual feature from traditional classifiers and is unable to make recognition of complex human actions using advanced spatio-temporal feature. To address this problem, the research team proposed a coding technique that converts poses into feature images, extracts high-level feature from the feature images and feeds them into a feature recognition system for recognition. The results show that the method is able to recognize human actions with high recognition accuracy [9]. Silva and Marana argue that existing human pose extraction uses straight lines to represent body parts in a two-dimensional human model. The team proposes an improved method based on existing human pose extraction, which maps each segment of a 2D pose to a point to extract spatial feature. The results of the study indicate that the method is effective in improving the recognition rate [10].

Table 1: Literature review

Study	Method	Application	Key Findings	Performance Comparison	References
Liu L et al.	Dual-view 3D pose estimation without camera parameters	Human pose estimation in dual views	Extracts joint coordinates from dual 2D images, inputs to 3D regression network	High accuracy in human pose recognition	[3]
Ferreira B et al.	Skeleton and deep semantic feature training system	Human activity detection and filtering	Detects activities and removes redundant repetitions	Accurate recognition with effective redundancy filtering	[4]
Liu H et al.	Elliptical Gaussian coordinate encoding	Action recognition in skeletal models	Uses heatmap differences for precise pose identification	High recognition accuracy on various datasets	[5]
Vishwakarma	Dual-wavelet	Human action	Extracts motion	Consistently high	[6]

D K	transformation	recognition in videos	feature using wavelet transform	accuracy across datasets	
Tian L et al.	Generative Adversarial Network (GAN)	Pose estimation with occlusion	Cascade and graph-based networks handle lighting and occlusion	High accuracy even with occluded keypoints	[7]
Zhang X et al.	Structure-aware network	3D joint correction in skeletal models	Reduces endpoint and bone length errors	Enhanced accuracy with reduced joint errors	[8]
Ht A et al.	Pose encoding to feature images for high-level feature extraction	Complex human behavior recognition	Converts pose to feature images for advanced feature recognition	High accuracy in complex activity recognition	[9]
Silva V et al.	Spatial feature extraction from mapped pose segments	2D human pose representation improvement	Maps 2D segments to extract spatial feature	Improved recognition rates	[10]

In summary shown in Table 1, many scholars have conducted research in the field of human pose recognition and achieved significant results, but there are still some limitations. Firstly, many methods rely on multi view inputs or high-quality data, and the recognition accuracy may decrease in single view or complex backgrounds. Secondly, encoding methods based on skeleton or feature images have limited performance in dealing with large occlusions or complex non repetitive actions. Some methods have high computational complexity and are not user-friendly for real-time applications, and models such as generative adversarial networks rely heavily on training data, increasing the complexity of model construction and training. In addition, information loss during the encoding process may affect recognition performance, especially in situations where there are rich pose details or diverse pose changes, limiting the applicability and accuracy of these methods. The deep residual network combined with the improved algorithm of Involution is used for feature extraction, creating a human skeleton network to recognize and classify human actions.

3 Martial arts movement recognition based on human posture estimation

With the development of the Internet, human body recognition technology has been vigorously developed and is widely used in motion analysis, video surveillance and other fields. In this study, Involution's feature extraction network is first proposed for lightweight human pose estimation, which is combined with existing human pose estimation models to recognize human pose. The extracted feature is then fed into a longand short term memory neural network.

3.1 Involution feature extraction network based human pose recognition

In the field of computer imaging, the main indicator of the strength of a neural network's performance is the strength of its feature extraction performance. By analysing the existing convolutional kernels, two drawbacks are found, one is that the perceptual field is difficult to capture feature dependencies over long distances due to the limitation of the convolutional kernel size.

The other is that the information between channels is rather complex and redundant. To solve this problem, this research proposes a new neural network operator Involution to assist feature extraction [11]. Involution is spatially specific, spatially specific in that it increases the receptive field by increasing the size of the convolution kernel, and channel invariant in terms of channels. Channel invariance allows neural networks to share in terms of channel dimensions, thus solving the problem of complex redundancy of information between channels. The main function of Involution is the reallocation of arithmetic power, which allows the computer to perform optimally.

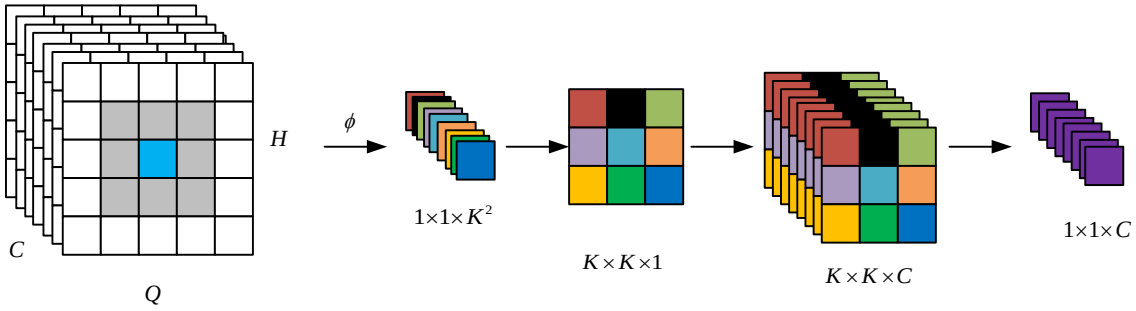


Figure 1: Generate convolutional kernel diagram

Figure 1 shows the process of generating a convolution kernel by Involution. Firstly, a multi-channel feature map is input and the feature vector of any point in the feature map is selected. Multiplying this kernel with the feature vector adjacent to the point gives the $K\times K\times C$ feature map, and finally the $K\times K\times C$ kernel is superimposed to obtain the final output feature map, with Involution generating different kernels for different locations and sharing a single kernel at the same location on the channel [12]. The traditional Convolution kernel counts and Involution counts are shown in Equation (1).

$$\begin{cases} 1\times1\times C_0\times C_i\times K\times K \\ H\times Q\times K\times K\times G \end{cases} \tag{1}$$

In Equation (1), 1×1 denotes the convolution kernel shared at $H\times Q$ pixel points, C_0 denotes the number of channels in the output, C_i denotes the number of channels in the input, K denotes the size of the convolution kernel, and G denotes the number of groupings. The number of channels is usually larger, the number of groups is usually much smaller than the number of channels, and the size of the Involution convolution kernel does not have a number of channels, so the ability to capture long distance feature can be enhanced by increasing the size of the convolution kernel. Involution is able to increase the accuracy of the model by this method while reducing the number of model parameters and the amount of computation [13].

This research uses a deep residual network combined with an Involution modified algorithm for feature extraction. The neuron learning feature maps of the general neural network and ResNet are shown in Figure 2.

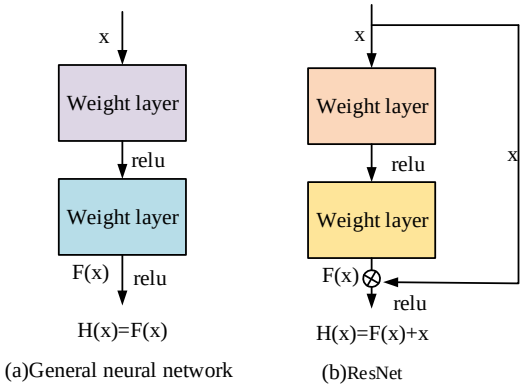


Figure 2: Neuron learning feature map

Figure 2(a) shows the process of learning feature in the fully-connected layer of a general neural network, which can be seen to be learning directly on the mapping between input and output. Figure 2(b) represents the process of learning feature in the fully-connected layer of ResNet, which can be seen to learn the residuals between the input and output. The InNet unit still has the same structure as the ResNet unit, with three convolutional layers in series, the first layer still reduces the dimension of the input channel, and the second layer uses the convolutional kernel generated by Involution to replace the original the second layer uses the convolution kernel generated by Involution to replace the original convolution kernel. The third layer is to expand the reduced-dimensional feature to the desired size. This improvement improves the feature extraction capability of InNet and also reduces the number of parameters and computational effort [14]. Convolution and Involution are shown in Equation (2).

$$\begin{cases} K^2C^2 \\ \dfrac{C^2+K^2GC}{r} \\ HQ\times K^2C^2 \\ HQ\times\dfrac{C^2+K^2GC}{r}+HQ\times K^2C \end{cases} \tag{2}$$

Equation (2) shows the number of parameters for Convolution and Involution and the amount of calculation for Convolution and Involution. Where H is the height of the input feature map, Q is the width of the input feature map, C is the number of input feature map channels, and r is the channel reduction ratio. The Involution Pose Estimation Net (IPEN) is used as the basis for extracting feature for the convolution kernel by Involution as shown in Figure 3.

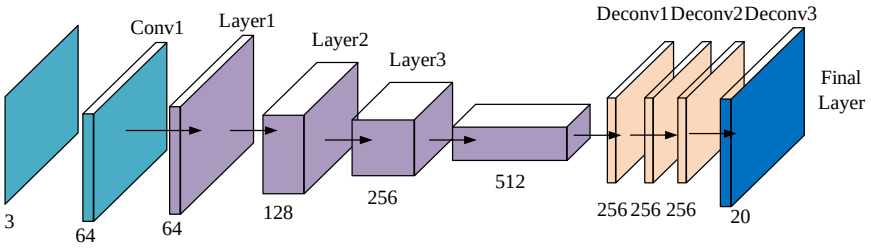


Figure 3: Convolutional kernel feature extraction graph

As shown in Figure 3, firstly, the input is a 3-channel image, and after passing through the first convolutional layer Conv1, the number of channels increases to 64. Next, after passing through three consecutive convolutional layers, Layer1, Layer2, and Layer3, the number of channels in the feature map increases to 128, 256, and 512, respectively. After completing the three convolutional layers, it enters the deconvolution stage (Deconv1, Deconv2, and Deconv3). In the deconvolution stage, each deconvolution layer gradually reduces the number of channels in the feature map from 512 to 256, resulting in a final output of 20 channels. The human pose recognition network uses InNet as the feature extraction network of the recognition network, and after expanding it by ordinary convolutional layers, Involution is used to extract feature information from the image, and the nodes are obtained by three convolutional layers that act as regressors. The metrics used to evaluate the model are Object Keypoint Similarity metrics, as shown in Equation (3).

$$Oks_p=\frac{\sum_l \exp\left\{-d_{pl}^2/2S_p^2\sigma_I^2\right\}\delta(v_{pl}=1)}{\sum_l \delta(v_{pi}=1)} \tag{3}$$

In Equation (3), p represents the person ID, l represents the number of keypoints S_p represents the current person's scale factor, v_{pl} represents whether the l th key point of the p th person is observable, d_{pl} represents the rated Euclidean distance between each person and each person's predicted joint point, σ_I represents the normalisation factor for the I th skeletal point, and δ represents the function that calculates the visible point [15].

3.2 Research on martial arts movement recognition based on human posture

Since traditional neural networks often fail to achieve the desired results when processing data with temporal information such as video and audio, Recurrent Neural Network (RNN) was introduced to process the data. Recurrent Neural Networks are capable of outputting information that is dependent on both present input and historical records. The structure of an RNN is shown in Figure 4.

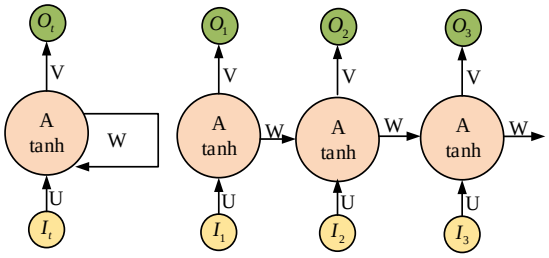


Figure 4: Structure diagram of recurrent neural network

Figure 4 represents the structure of an RNN, where A represents a single neural network unit, O_t represents the output at the time point, and I_t represents the input at the time point. U, V and W represent the different network weights respectively. The Long Short Term Memory Neural Network is an improvement on the RNN, which can process time series like the RNN and has a similar structure to the RNN, but the recurrent structure in the LSTM network is not the same as that of the RNN. The recurrent structure consists of three parts respectively three gate structures, one unit state and four neural network layers [16]. The structure of the LSTM neural network is shown in Figure 5.

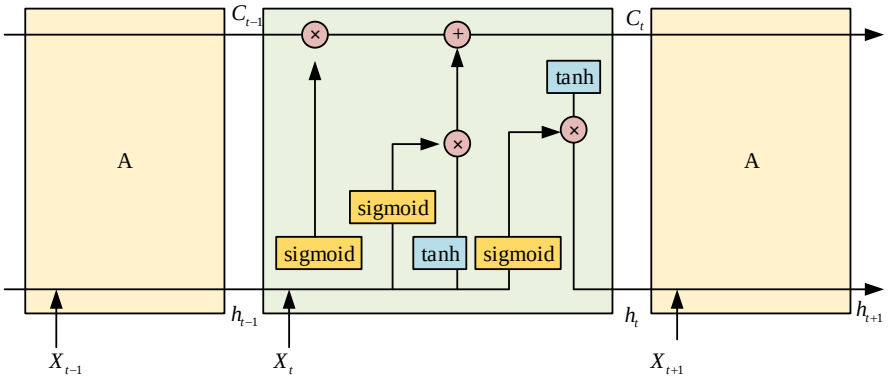


Figure 5: LSTM neural network structure diagram

As can be seen from Figure 5, the entire recurrent structure consists of a short-term memory module, a current memory module and a long-term memory module. In the current memory module, there are four neural network layers, three of which are single-layer sigmoid feed forward neural networks and one is a single-layer tanh feed forward neural network, and the LSTM neural network is mainly used to filter the feature information and determine the retention status through three gate structures: input gate, output gate and forgetting gate. Each gate structure is composed of a vector operation and a sigmoid neural network layer. Classify human joints using a human pose recognition network combined with human joint data, as shown in Figure 6.

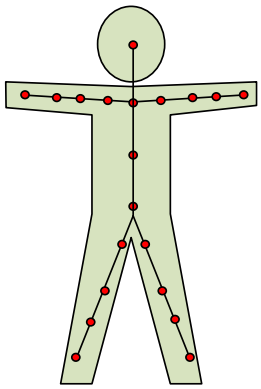


Figure 6: Skeleton division diagram of the human body

Figure 6 shows the division of the human skeleton. The importance of different bones to the human body varies. If bone joints are divided into 20 joints according to their importance, a sequence of human posture can be represented by equation (4) [17].

$$\begin{cases} S = \{K_1, K_2, \ldots, K_t\} \\ K_t^j = (x_j, y_j, z_j), 1 < j < M \end{cases} \tag{4}$$

In Equation (4), S represents the sequence of human skeletal articulation points, K_t represents the skeleton at t, M represents the number of articulation points, (x, y, z) represents the coordinates of the articulation points, and j represents the j th articulation point in the skeleton at t. The state of the human skeleton at each moment is coded into a network, and the skeleton joints at each moment change with time [18]. Define the interaction network of articulation points at different moments in time as shown in Equation (5).

$$SAN_t = (V_t, E_t) \tag{5}$$

In Equation (5), V_t denotes the set of vertices in the network at the moment of t and E_t denotes the set of edges in the network at the moment of t. For the skeleton state at the same moment, the joints are connected to each other and the relationship between the joints is expressed by calculating the Euclidean distance between each joint as shown in Equation (6).

$$d(i, j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{6}$$

In Equation (6), i is any one of the joints except j. Since the human body completes the action, it is not determined by individual joints, but by the overall coordination of the human body, just using the Euclidean distance cannot highlight the relationship between each joint well, so the human body is divided into different five parts, and different weight coefficients are set according to different parts as shown in Equation (7).

$$w(i, j)\begin{cases} d(i, j) \times a_1, 1 \le i, j \le 4 \\ d(i, j) \times a_2, 5 \le i, j \le 8 \\ d(i, j) \times a_3, 9 \le i, j \le 12 \\ d(i, j) \times a_4, 13 \le i, j \le 16 \\ d(i, j) \times a_5, 17 \le i, j \le 20 \end{cases} \tag{7}$$

In Equation (7), a_1 and a_2 represent the weight coefficients of the left and right arms, a_3 and a_4 represent the weight coefficients of the left and right leg parts, a_5 represents the weight coefficient of the torso part. After the skeleton nodes were constructed, the feature information of the image was extracted by CNN local convolution. The extracted feature data is then fed into the LSTM for processing, and the feature data is

filtered and judged by various gates. Each LSTM cell has an input gate, an output gate and an oblivion gate, and the input gate is calculated as shown in Equation (8).

$$i_t = g(W_{x^i} x_t + W_{h^i} h_{t-1} + b_i) \tag{8}$$

Equation (8) represents the input gate, x_t represents the input value of the network at the current time and h_{t-1} represents the output value of the network at the previous time. b_i denotes the input gate constant parameter. The output gate is calculated as shown in Equation (9).

$$f_t = g(W_{x^f} x_t + W_{h^f} h_{t-1} + b_f) \tag{9}$$

Equation (9) represents the output gate, x_t represents the input value of the network at the current moment, and b_i represents the output gate constant parameter. The formula for the forgetting gate is shown in Equation (10) [19].

$$o_t = g(W_{x^o} x_t + W_{h^o} h_{t-1} + b_o) \tag{10}$$

Equation (10) represents the forgetting gate and h_{t-1} represents the output value of the network at the previous moment. b_o denotes the constant parameter of the forgetting gate. In the IPN recognition technique for the skeleton, the human skeleton at each moment is encoded as a network, and the weights of the edges are calculated based on the distance between any two joints in the network as shown in Equation (11).

$$d(i,j) = 1 \Big/ \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{11}$$

In Equation (11), i and j denote the nodes in the network and (x, y, z) denotes the 3D coordinates of the node, it can be seen that the weights are expressed as the reciprocal of the Euclidean distance. In order to represent the transformation of the nodes in the network in time, metrics such as proximity centrality are introduced for evaluation, as shown in Equation (12).

$$CC_i = \frac{N-1}{\sum_{j \in U, j \neq i} d(i,j)} \tag{12}$$

In Equation (12), N is the number of nodes in the network and U is the set of all nodes in the network. Proximity centrality indicates how close the node is to each of the other nodes in the network; the closer the node is, the greater its closeness centrality, but the same node will change over time and its centrality will change as well. The eigencentricity vector of the network nodes is analysed as shown in Equation (13).

$$EC_i = c \sum_{j=1}^{N} A_{ij} EC_i \tag{13}$$

In Equation (13), EC_i represents the eigenvector centrality and sets its initial value to 1, represents the adjacency matrix in the network, A_{ij} represents the connection between nodes i and j, and the initial vector of EC_i is cyclically multiplied with A to obtain the value of EC_i. The stability of the network is usually assessed by the average degree as shown in Equation (14) [20-21].

$$K_i = \frac{\sum_{i=1}^{N} K_i}{N} \tag{14}$$

In Equation (14), K_i represents the weighted degree of the node i. The topological properties of the network nodes are combined with the topological properties of the network to represent the entire skeleton of the action network. A sample skeleton of all actions is shown in Equation (15).

$$Y_{input} = [\theta_1, \theta_2, \theta_3, \ldots, \theta_{u-1}, \theta_u] \tag{15}$$

In Equation (15), Y_{input} denotes the input to the LSTM and u denotes the number of samples. θ_u denotes the feature vector in u. The samples are classified by this method to identify human actions. The process of this model is as follows. Firstly, the Involution operation dynamically generates convolutional kernels that adapt to feature maps, enhancing the ability to capture long-distance feature and reducing information redundancy between channels. By combining this network structure with a deep residual network, an improved InNet was formed, which can efficiently extract feature and reduce the number of model parameters. Subsequently, LSTM was used to process time series data and analyze the dynamic changes of human joint points. Joint points are classified according to their importance, and Euclidean distance is calculated to describe the relationship between joints. The sensitivity of action recognition is improved by setting weights for different parts.

4 Performance analysis of martial arts movement recognition based on human posture estimation

The first section of this chapter analyses Involution's downsampling capability and then analyses the accuracy of the model under different dataset sizes to determine the best data size to calculate its feature extraction time. The second section provides an analysis of the introduction of

LSTM networks to compare the models under different algorithms.

4.1 Performance analysis of human pose recognition based on involution feature extraction network

To verify the performance of this feature extraction network using InNet as the recognition network, InNet was compared with ResNet. The CPU used in this experiment is Intel(R) Xeon® Gold6226@2.7GHz, the GPU used is NVIDIA GeForce Tesla V100S, and the memory is 32 GB. The learning rate of the model is set to 0.001 and decays by 0.1 every 10 epochs to gradually reduce the learning rate. The batch size is 32 to ensure efficient memory usage during the training process. The optimizer uses Adam because of its adaptive learning rate feature, which can handle sparse gradient problems. The loss function uses cross entropy loss, which is suitable for multi class classification tasks. Using L2 regularization, the weight decay parameter is set to 0.0001 to reduce the risk of overfitting. In terms of data augmentation, methods such as random cropping, rotation, and translation are applied during training to improve the model's generalization ability. In terms of feature extraction network, the number of layers in the Involution network is set to 5, and the number of channels is set to 128 to evaluate performance. In terms of LSTM configuration, the number of units is set to 256 to better capture time series feature. The training cycle is set to 100 epochs, using 20% of the data as the validation set to monitor model performance and prevent overfitting. When the number of layers in the network is small, Involution has less compression power, but the accuracy is improved. As the number of layers increases, Involution has a good improvement in compression, but with some loss of accuracy.

Table 2: Argument reduction capability of revolution

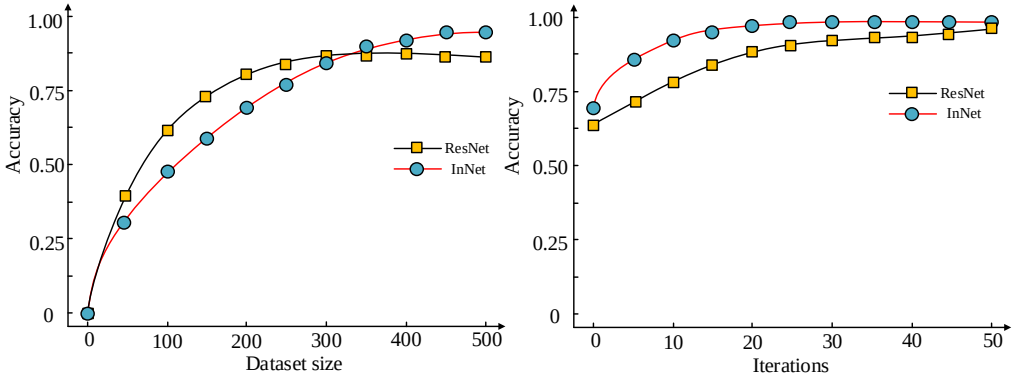
Method	Input size	Param	FLOPs
ResNet-Q32	256 x 192	28.4M	7.2G
	384 x 288	28.4M	16.5G
ResNet-Q48	256 x 192	63.9M	14.7G
	384 x 288	63.9M	32.5G
InNet-Q32	256 x 192	17.1M	4.7G
	384 x 288	17.1M	10.1G
InNet-Q48	256 x 192	38.7M	7.9G
	384 x 288	38.7M	20.4G

In Table 2, Q32 indicates that the number of channels for each convolutional layer is set to 32, and Q48 indicates that the number of channels for each convolutional layer is set to 48. Table 2shows the table of Involution's degree-reducing capacity, InNet for using Involution instead of Convolution, from the table it can be seen that ResNet's Param is 28.4M and 63.9M, InNet's Param is 17.1M and 38.7M, ResNet under different methods, different sizes of The FLOPs of different sizes for ResNet were 7.2G, 16.5G, 14.7G and 32.5G, respectively, and the FLOPs of different sizes for InNet were 4.7G, 10.1G, 7.9G and 20.4G, respectively, under different methods. The experimental results indicated that the InNet method using Involution instead of Convolution reduced the number of parameters and computation by about 40%, indicating that Involution has good capability of reducing parameters. Compare the computational complexity of different methods.

As shown in Table 3. InNet reduces its dependence on large convolution kernels through Involution, while ResNet relies on deep residual structures, and LSTM uses recursive structures to process time series. InNet has relatively low memory usage because it uses smaller feature maps, while ResNet requires more memory due to its deep structure. LSTM also increases memory requirements when processing long sequences. The latency of InNet is moderate, influenced by input size and sequence length. ResNet and LSTM can cause high latency when processing large inputs or long sequences.

Table 3: Comparison of computational complexity

Model	Processing Flow	Memory Usage	Latency
InNet	Utilizes Involution instead of convolution for feature extraction, followed by LSTM for sequence analysis	Low to moderate, depending on feature map size and number of channels	Moderate, influenced by input feature map size and time steps
ResNet	Employs multiple residual blocks for feature extraction, followed by fully connected layers for classification	High, especially in deeper networks	High, particularly when processing large input sizes
LSTM	Uses a recurrent structure to handle sequence data	High, due to the need to store hidden states and input sequences	High, especially with long sequences and multiple feature

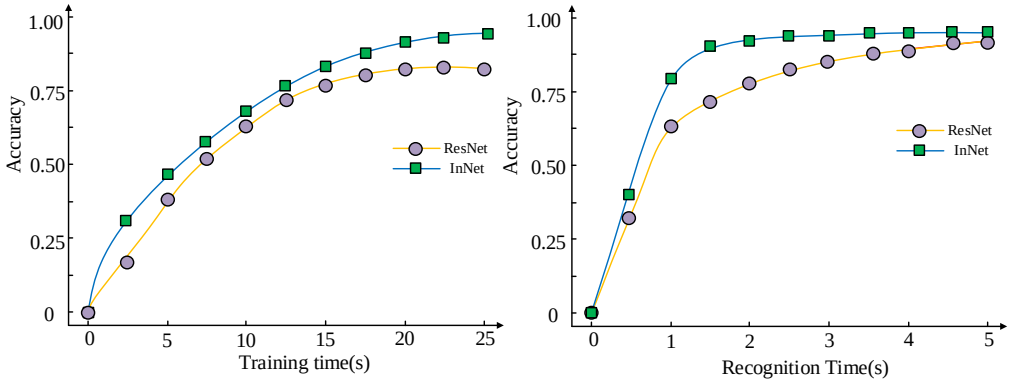


(a)The relationship between dataset size and accuracy (b)The relationship between the number of iterations and accuracy

Figure 7: Model accuracy of RseNet and InNet

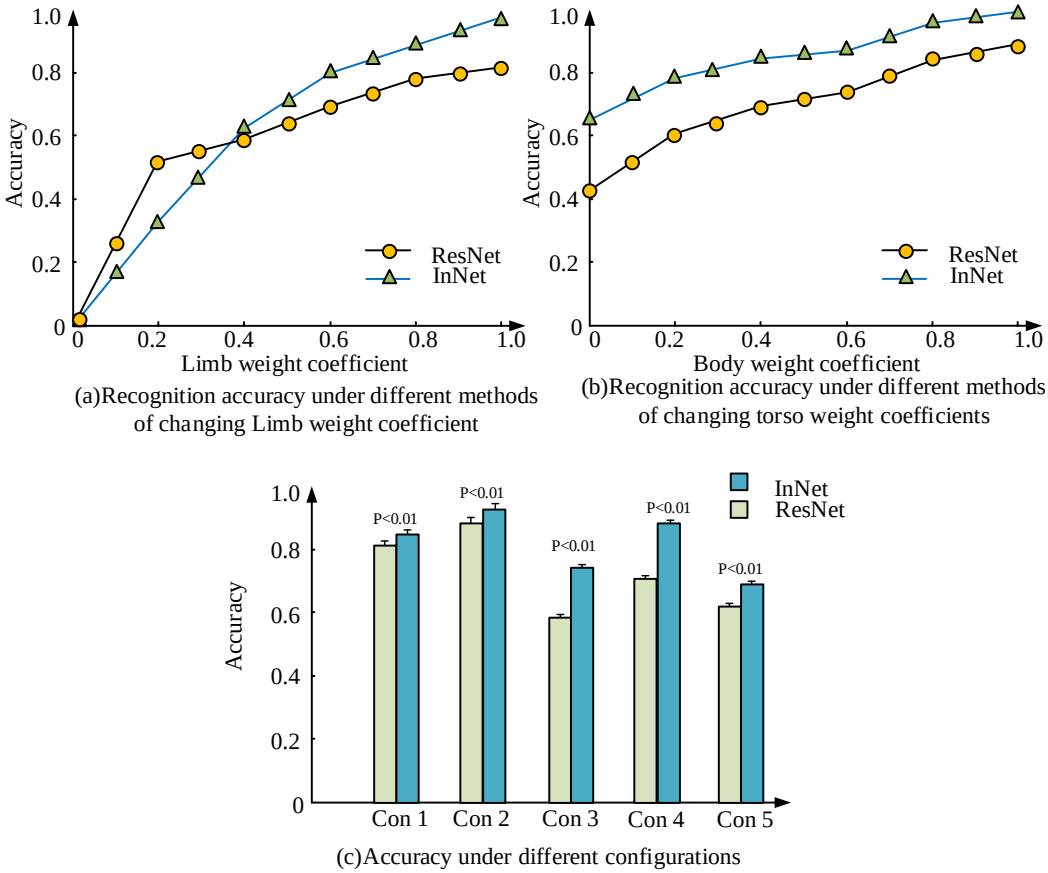
As can be seen from Figure 7(a), the extraction performance of both methods is better when the dataset is larger and contains more species. Since the number of Involution parameters and the amount of computation in InNet is less compared to that of the traditional Convolution in ResNet, the accuracy of InNet is still increasing when the size of the dataset reaches a certain amount, ResNet has levelled off. From Figure 7(b), it can be seen that with the selected dataset size, InNet has been able to achieve the best recognition performance with a small number of iterations, and ResNet has not yet achieved the best performance with the number of iterations where InNet's performance has reached its best, and reaches a point where when the performance no longer changes, it is still lower than InNet's performance. It can be seen that InNet has good performance in feature extraction. Judging the goodness of a model cannot only focus on its accuracy, its training time and recognition time is still an important indicator as shown in Figure 8.

Figure 8(a) shows the change in model performance for both methods as the training time increases. It can be seen that the training time for InNet is a little longer than that for ResNet, the situation is due to the fact that InNet uses a larger dataset during training and only a large enough dataset can satisfy InNet to allow it to train to achieve the best performance. Figure 8(b) shows the change in model accuracy as the recognition time increases for both methods. It can be seen that InNet is able to use a small amount of time to achieve the best recognition accuracy on images when recognizing. The results of the study indicate that the training time for InNet is slightly longer but within acceptable limits and that the overall performance of InNet is better than that of ResNet.



(a)The relationship between training time and accuracy (b)The relationship between recognition time and accuracy

Figure 8: Analysis of training time and recognition time for two models



(a)Recognition accuracy under different methods of changing Limb weight coefficient

(b)Recognition accuracy under different methods of changing torso weight coefficients

(c)Accuracy under different configurations

Figure 9: Model accuracy under different weight coefficients and configurations

4.2 Performance testing of a human posture-based martial arts movement recognition model

A selection of martial arts moves is identified, including the lunge punch, punch and pop kick, horse stance punch, horse stance frame punch and top stomp kick. The five movements are renamed as Movement 1, Movement 2, Movement 3, Movement 4 and Movement 5 respectively. The weighting coefficients for the left and right arms, the left and right legs and the torso were assigned to compare the influence of each part of the skeleton on the recognition system. This is shown in Figure 9.

Figure 9 (a) shows the recognition accuracy for different methods with a value of 1 for the torso weighting factor a_3 and changing the weighting factor for the extremities. Figure 9(b) shows the recognition accuracy for different methods of varying the torso weighting coefficients when the values of the limb weighting coefficients a_1 and a_2 are set to 1. It can be seen that when the limb weighting coefficients are changed, the accuracy rate increases significantly with the increase of limb weighting coefficients and stabilises when the limb weighting coefficients reach 0.8. When the weighting factor of the limbs was changed, the change in accuracy was minimal when the weighting factor of the torso was changed. The experimental results show that the influence of the limbs on the accuracy is greater than the influence of the torso on the accuracy. Figure 9 (c) Accuracy rates for five different weighting factors not chosen named configurations 1 to 5 respectively, at different weighting factors. Configuration 1 has a torso weight coefficient of 0.2 and limbs weight coefficient of 0.8, Configuration 2 has a torso weight coefficient of 0.6 and limbs weight coefficient of 0.8, Configuration 3 has a torso weight coefficient of 0.6 and limbs weight coefficient of 1.0. Configuration 4 has a torso weight coefficient of 0.4 and limbs weight coefficient of 0.8. Configuration 5 has a torso weight coefficient of 0.4 and limbs weight coefficient of 0.6. It can be seen that the accuracy of recognition is maximised when the torso weighting factor is 0.6 and the limb weighting factor is 0.8($P<0.01$). A comparison of recognition for different actions at different weighting factors is shown in Figure 10.

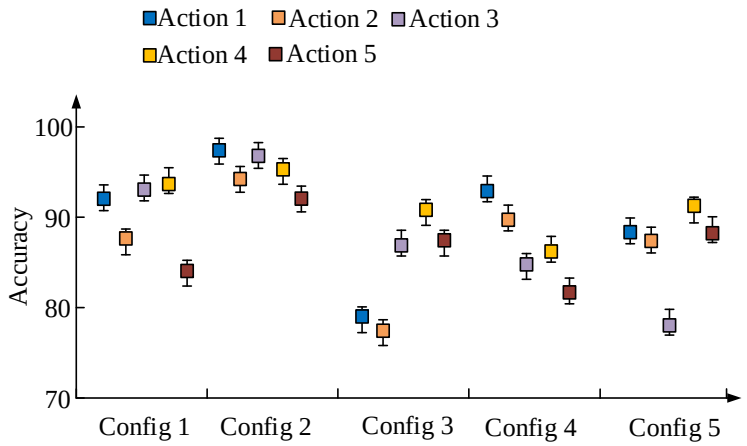


Figure 10: Accuracy of five different actions under five weight coefficients

Table 4: Recognition accuracy of different algorithms on datasets

Method	Eigen	STOP	DMM & HOG	Actionlet	JAS & HOG2	InNet-LSTM
Data 1 Accuracy (%)	81.3	82.5	85.3	87.6	83.5	90.6
Data2 Accuracy (%)	76.5	81.4	86.2	88.6	87.9	93.6

From Figure 10, the accuracy of five different actions with five weighting factors, it can be seen that the action with weighting configuration 2 has the highest average accuracy and has a more stable performance. The other weighting configurations all have large fluctuations in accuracy and show unstable performance. Considering both stability and accuracy, the weights used to construct the human skeleton were set to a torso weighting factor of 0.6 and an extremity weighting factor of 0.8. Different methods were introduced to compare with the method used in this study, and the MSR Action 3D dataset was chosen for this experiment. This dataset contains 6000 images specifically designed for human action recognition tasks, covering multiple explicit action categories including walking, running, jumping, and sitting. The image size of each sample is 640x480 pixels, ensuring clarity and detail. The sample distribution of these action categories is uneven, with more samples for walking and running, and relatively fewer samples for jumping and sitting, which may affect the training effectiveness and performance of the model. Each image is equipped with clear labels to indicate the corresponding action category, ensuring the accuracy of the training data. In addition, the dataset generates additional samples through data augmentation techniques, including random rotation, flipping, and scaling, to enhance the model's generalization ability. Different algorithms were used to divide the dataset into Dataset 1 and Dataset 2, and the recognition accuracy on different datasets is shown in Table 4.

According to Table 4, in dataset 1, the accuracy of Eigen method is 81.3%, STOP method is 82.5%, DMM&HOG method is 85.3%, Actionlet method is 87.6%, and JAS&HOG2 method is 83.5%. The accuracy of the InNet LSTM method is 90.6%. In dataset 2, the accuracy of each method is higher than in dataset 1. The accuracy of the proposed methods in this study was higher than the other methods. To further validate the accuracy of the InNet-LSTM method, the accuracy of the different methods was verified under different dataset sizes. This is shown in Figure (11).

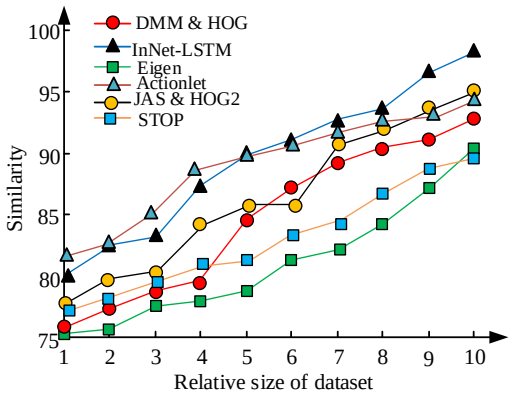


Figure 11 Accuracy of different methods under different dataset sizes

The accuracy of InNet-LSTM is lower than that of Actionlet method when the dataset is small, but when the dataset increases to a certain level, the accuracy of InNet-LSTM is greater than that of other methods.

5 Discussion

Human motion recognition relies on video frame by frame decomposition and manually designing motion feature to achieve recognition. The martial arts action recognition system based on Involution feature extraction network and LSTM proposed in the study optimizes recognition accuracy and efficiency by reducing the computational complexity of traditional convolutional networks. The experimental results show that compared with traditional convolutional networks such as ResNet, Involution significantly improves accuracy while reducing the number of parameters, especially on datasets of different sizes, with an average increase of 5% in object keypoint similarity and 8% in accuracy in the test set. This is due to the advantage of LSTM in time series modeling, which enables the system to better understand the dynamic changes in action sequences, especially achieving an accuracy gain of about 15% in complex martial arts action recognition. The innovation of InNet LSTM lies in using Involution instead of traditional convolution to achieve lightweight and efficient feature extraction, and combining LSTM for temporal modeling to capture motion dynamics. This method outperforms ResNet in accuracy, resource utilization, and computation time, and is suitable for martial arts action recognition and other dynamic scenarios. It has broad applicability and efficient real-time processing capabilities. However, there are still limitations when dealing with unstructured random actions. Due to the limitations of existing equipment, higher performance hardware can be introduced in the future to optimize training speed and expand the dataset size to enhance the system's generalization ability.

6 Conclusion

In response to the problem of manually designing motion feature for recognition, which consumes energy and has very low recognition efficiency, research is conducted on improving human pose estimation based on deep learning. Firstly, Involution is proposed as a feature extraction network for light weighting of human pose estimation, and each joint point of the human body is labelled and classified separately. The experimental results show that the InNet method, which uses Involution instead of Convolution, decreases the number of parameters and the computational effort by about 40%. Comparing this method with other methods, the accuracy of the Eigen method is 81.3%, the STOP method is 82.5%, the DMM & HOG method is 85.3%, the Actionlet method is 87.6% and the JAS & HOG2 method is 83.5%. The accuracy of the InNet-LSTM method was 90.6%. It can be seen that the method proposed in this study has a high performance. However, there are still shortcomings in this study. When constructing a human skeleton model, the weights between the joints are determined by the distance between the joints, and the evaluation indicators are too single. And the research was conducted in a laboratory environment. Future research is considering using more indicators to construct human skeleton models and applying them to practical applications to test the performance of the models.

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Optimization of Elman Neural Network Using Genetic Algorithm for Construction Cost Estimation and Overspending Risk Analysis

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Keywords: neural network, construction cost estimation, overspending risk, Elman network, genetic algorithm

Received: November 14, 2024

This study proposes a model based on the Elman neural network and improves it using a Genetic Algorithm (GA) to increase the accuracy of construction cost estimation and accurately analyze the overspending risk. First, an index system containing multiple dimensions such as building features, structural features, project positioning, and project environment is constructed to comprehensively capture the key factors affecting construction cost and overspending risk. Second, the Elman neural network's structure and operation are thoroughly examined, and the GA optimizes the network's weights and thresholds to improve the model's predictive power. On the training set, the optimized GA-Elman model demonstrates great prediction accuracy, with relative error (RE) percentages between predicted and true values typically falling within ±1%. On the test set, the GA-Elman model performs better than the original Elman model in both difference and RE, with a Mean Absolute Percentage Error of 2.75%, a decrease of 18.4% compared to the Elman model. These results indicate that the GA-Elman model is more accurate in cost prediction and more effective in identifying potential overspending risks. This study provides a powerful tool for cost control and budget management in the construction industry and a new perspective on the application of neural networks in construction economics.

Povzetek: Razvit je model za ocenjevanje stroškov gradnje in analizo tveganja prekoračitve stroškov, ki temelji na Elmanovi nevronski mreži, optimizirani z genetskim algoritmom. Model je močno orodje za obvladovanje stroškov in upravljanje proračuna v gradbeništvu.

1 Introduction

In the construction industry, cost estimation is the core link of project management, directly related to the project's economic benefits and risk control. Traditional cost estimation methods rely on expert experience and historical data. Still, such methods are often influenced by subjective judgment and are difficult to adapt to the rapidly changing market environment and complex and changing engineering conditions [1-3]. Traditional cost estimation procedures encounter increasing challenges as building projects get larger and more complicated. As a result, new techniques and methodologies must be introduced immediately to increase estimation efficiency and accuracy [4, 5].

With the advancement of machine learning (ML) and artificial intelligence in recent years, neural networks have shown to be a valuable tool for tackling challenging forecasting issues. Because of their benefits in processing sequence data, recurrent neural networks (RNNs) are widely applied across various fields, such as natural language processing and time series prediction [6-8]. The Elman neural network, as a kind of RNN, enhances the network's memory ability by introducing the context layer, which makes it perform well in dealing with time-dependent sequence data [9].

This study explores the application of neural networks in construction cost estimation and overspending risk analysis. A new approach to cost estimating is presented, which involves creating a building cost model based on the Elman neural network and using a Genetic Algorithm (GA) to optimize it. This approach can increase cost estimating accuracy while evaluating potential overspending risk analysis and offering construction project management scientific decision assistance.

The main contribution of this study is the proposal of a construction cost estimation model based on the Elman neural network combined with a GA, specifically:

Firstly, GA is applied to optimize the Elman neural network, utilizing GA to improve the weights and thresholds of the neural network, thereby enhancing the model's prediction accuracy and generalization ability. As a global search optimization tool, GA can avoid the problem of falling into local optimal solutions that is common in traditional training processes.

Secondly, by constructing a comprehensive index system and integrating it with the Elman neural network, a more accurate method for construction cost prediction is provided compared to traditional models. Furthermore, the model's applicability in complex construction projects is effectively improved through further optimization with GA.

Finally, the study focuses on the prediction of construction costs and proposes a new method for assessing cost overrun risks. Through the model's dynamic memory mechanism, it is possible to analyze the impact of historical data on future costs, identify potential risk

factors in advance, and provide decision support for project management.

2 Related work

In the construction industry, the accuracy of cost prediction is critical for the project's success. With the development of information technology, more and more researchers began to explore how to use advanced technical means to improve cost prediction accuracy. Mahmoodzadeh et al. forecasted the geological conditions, construction duration, and cost of tunnels using Gaussian Process Regression (GPR), Support Vector Regression (SVR), and decision tree models. Through 50% cross-validation to evaluate the model's performance, it was found that GPR was superior to SVR and decision trees in prediction accuracy. Hence, GPR was recommended to predict future tunnel projects' geological and construction time costs [10]. Alshboul et al. used an ML algorithm to predict the cost of green buildings, considering the influence of related attributes of soft and hard costs. The evaluation results showed that eXtreme Gradient Boosting (XGBoost) performed best in accuracy, followed by the deep neural network (DNN) and random forest (RF) [11]. These models could be used as decision-support tools for construction project managers and practitioners to promote the development of automation research in the green building industry.

Because neural networks can handle complicated nonlinear interactions, they have emerged as a potent tool for cost prediction problems. Pham et al. proposed an ML and optimization framework incorporating artificial neural networks (ANNs) and gradient boosting models to estimate construction costs and optimize costs under budget constraints rapidly [12]. Goodarzizad et al. improved the accuracy of construction labor productivity models for concrete pouring operations through a hybrid model developed by combining ANN and Grasshopper optimization algorithms [13]. The study helped to improve project efficiency, increase labor productivity, and reduce costs. Kim et al. introduced an autoregressive integrated moving average (ARIMA)-ANN model to predict construction costs. They found that the model provided more accurate predictions in most cases, especially for long-term forecasting time limits, than standalone ARIMA or ANN models [14]. The main contents of the above research are summarized in Table 1.

Table 1: Summary of relevant research contents

Model	Method	Dataset	Key results
GPR, SVR, Decision tree	ML method is used to predict tunnel geological conditions, construction period, and cost. The model's performance is evaluated by 5-fold cross-validation.	Tunnel project data	GPR has better prediction accuracy than SVR and decision tree. Meanwhile, it is recommended for geological and time cost prediction of future tunnel projects
XGBoost, DNN, and RF	By considering soft and hard cost attributes, ML methods are used to predict green building costs.	Green building-related data	XGBoost performs the best in prediction accuracy, with an accuracy of 0.96; This Is followed by DNN (0.91) and RF (0.87), which can provide decision support tools for the green building industry.
ANN, gradient boosting model	13 ML regression algorithms are employed to estimate construction costs and optimize costs under budget constraints	Construction configuration dataset	ANN and gradient boosting algorithms perform the best, estimating construction costs and required resources with 99% accuracy in less than 1 second of training time, and reducing costs by 7% through optimization.
Hybrid model (ANN+Grasshopper algorithm)	The combination of ANN and Grasshopper optimization algorithm improves the labor productivity model of concrete pouring operation.	Labor productivity data for 24 commercial office complex projects under construction in Iran	The project efficiency is improved, labor productivity is increased, and costs are reduced
ARIMA-ANN model	The ARIMA model is integrated with ANN to predict construction costs.	National and city-level construction cost index	In most cases, especially in long-term forecasting, hybrid models have higher prediction accuracy than ARIMA or ANN models used alone.

Although significant progress has been made in construction cost estimation, there remain substantial limitations in terms of generalization ability and overspending risk assessment. Specifically, many models rely on specific datasets, making it challenging to maintain prediction accuracy in new construction project scenarios. For instance, while models like GPR and XGBoost exhibit high prediction accuracy on particular datasets, their performance may decline significantly when applied to cross-dataset scenarios or when handling previously unseen complex situations. Existing research tends to focus more on cost prediction accuracy, with less emphasis on the quantification and identification of potential overspending risks. For complex construction projects, such models lacking risk assessment abilities could lead to delayed cost control decisions. To address these shortcomings, this study proposes a construction cost estimation model based on the Elman neural network, optimized with a GA. The GA enhances the model's global search capability by optimizing the initial weights and thresholds of the Elman neural network, thereby improving its prediction performance across different datasets and complex scenarios. The dynamic memory mechanism of the Elman neural network enables it to capture long-term dependencies in time-series data, allowing the analysis of cost trends and forecasting potential overspending risks. Moreover, by designing a comprehensive overspending risk index system, the model can quantitatively identify key factors that lead to cost deviations, providing a basis for risk prevention and control.

3 Construction cost estimation model based on elman neural network

3.1 Construction cost estimation and construction of overspending risk index system

The study focuses on assembly buildings. The selection of indexes affecting the cost and overspending risk is based on the principles of comprehensiveness, scientificity, a combination of quantitative and qualitative methods, dynamics, and operability. These indexes are chosen from four aspects: architectural features, structural features, project positioning, and project environment. The method of literature analysis is used for this selection. The quantification of qualitative indexes is carried out [15-17]. In constructing the cost estimation and overspending risk index system, the selection of each index is based on its correlation with construction costs and overspending risk. For example, in the case of exterior wall decoration, significant differences in the price and construction techniques of different materials exist. Paint is relatively inexpensive, while materials such as stone and glass curtain walls are more costly and have longer construction periods, potentially increasing the overspending risk [18]. Similarly, the technical personnel level directly influences construction efficiency and quality. Low technical levels may lead to rework and delays, thus increasing both cost and the probability of overspending [19]. Architectural features such as floor area and standard floor height determine material usage and construction complexity, directly affecting the total project cost. Structural features, including the prefabrication rate and component differentiation, relate to the efficiency and cost control capacity of prefabricated construction. Project environmental factors, such as project management level and transportation distance, reflect the impact of management efficiency and logistics on cost. These indexes are validated through literature analysis and practical engineering experience, demonstrating their key role in cost control and overspending risk, thereby providing a theoretical foundation for the model's scientific and comprehensive nature. The finalized index system for assembly construction cost estimation prediction is outlined in Table 2.

Table 2: Construction cost estimation and overspending risk index system and assignment of values

Primary index	Secondary index	Nature of the index	Assignment of qualitative index
Architectural features	Number of floors A1	Quantitative index	-
	Building area A2	Quantitative index	-
	Standard floor height A3	Quantitative index	-
Structural features	Structure type A4	Qualitative index	1=internally cast and externally hung shear wall structure; 2=stacked shear wall structure; 3=assembled monolithic frame structure; 4=assembled monolithic shear wall structure
	Foundation type A5	Qualitative index	1 = independent foundation; 2 = pile foundation; 3 = raft slab foundation; 4 = pile raft foundation; 5 = box foundation
	Prefabrication rate A6	Quantitative index	-

	Component type A7	Qualitative index	1 = laminated panels/air conditioning panels/drift windows/enclosures; 2 = prefabricated stairs; 3 = beams/columns/shear walls
	Differentiation degree of components A8	Quantitative index	-
Project positioning	Exterior wall decoration A9	Qualitative index	1=paint; 2=real stone paint; 3=glass curtain wall; 4=aluminum panel; 5=stone
	Interior wall decoration A10	Qualitative index	1=general plaster; 2=plaster; 3=large white; 4=latex paint; 5=wall tiles; 6=wallpaper
	Ground engineering A11	Qualitative index	1=concrete topping; 2=ordinary tiles; 3=flooring; 4=premium tiles
	Door and window type A12	Qualitative index	1=plastic steel window + steel door; 2=aluminum alloy window + steel door; 3=plastic steel window + fire door; 4=aluminum alloy window + fire door
Project environment	Technical personnel level A13	Qualitative index	1=excellent; 2=good; 3=medium; 4=poor
	Project management level A14	Qualitative index	1=excellent; 2=good; 3=medium; 4=poor
	Transportation distance A15	Quantitative index	-

In the above index system, the three indexes of architectural features are directly related to the building's physical size and construction complexity, affecting material costs and labor requirements. These in turn affect cost control and the risk of overspending. The indexes of structural features determine the structural stability and construction methods, significantly impacting material selection and supply chain management, thus correlating with the overspending risk. Project positioning includes qualitative indexes such as exterior and interior wall decorations, ground engineering, and window and door types. These choices affect the building's aesthetics and functionality while leading to increased costs, which may increase overspending risk if costs are not properly controlled. Moreover, indexes in the project environment reflect the efficiency of project management and the impact of external conditions on costs, which are key factors in cost control and risk management. This system helps to forecast costs more accurately while identifying and controlling factors that may lead to overspending.

In the above index system, the priority of each index varies depending on its impact on costs and overspending risks. To ensure that the indicator system can comprehensively and scientifically reflect the risk of cost overruns, the Analytic Hierarchy Process is used to assign weights to each index. The results are exhibited in Table 3.

Table 3: Index system weight

Primary index	Weight of primary index	Secondary index	Final weight
Architectural features	0.162	Number of floors A1	0.054
		Building area A2	0.054
		Standard layer height A3	0.054
Structural features	0.409	Structure type A4	0.128
		Foundation type A5	0.073
		Prefabrication rate A6	0.053
		Component type A7	0.069
		Differentiation degree of components A8	0.086
Project positioning	0.290	Exterior wall decoration A9	0.044
		Interior wall decoration A10	0.068
		Ground engineering A11	0.121
		Door and window type A12	0.057
Project environment	0.139	Technical personnel levelA13	0.073
		Project management level A14	0.046

		Transportation distance A15	0.020

In Table 3, structural features hold the highest weight among the primary indexes, accounting for 40.9%, indicating their most significant impact on both construction costs and overspending risk. Among these, A4 and A8 have relatively higher weights of 0.128 and 0.086, respectively, reflecting the crucial role of building structure complexity and differentiation in cost control. The project positioning index ranks second, accounting for 29.0%, with A11 having the highest weight of 0.121, emphasizing its importance in construction decoration costs. The weights for architectural features and project environment are relatively lower. However, among the secondary indexes, A13 and A2 stand out with weights of 0.073 and 0.054, respectively, highlighting their influence on construction efficiency and total cost prediction. This weight allocation method enables the index system to more scientifically reflect the contribution of various factors to cost and overspending risk, providing a solid foundation for subsequent model predictions and risk analysis.

3.2 Elman neural network modeling analysis

The Elman neural network's key feature is the incorporation of a context layer, which preserves the hidden layer's state from a previous time step [20]. This enables the Elman network to process time-series data, capturing the dynamics of the input data and the underlying temporal relationships, making it suitable for time-dependent data prediction tasks such as construction costs. The network creates a short-term memory mechanism by feeding past information back to the current moment, which enhances its ability to model nonlinearities in dynamically changing processes. Unlike traditional feed-forward neural networks, the Elman network has feedback connections between the hidden and context layers. These feedback signals allow the network to retain information from previous states, providing valuable contextual input for subsequent computations [21, 22]. Figure 1 depicts the Elman neural network's basic structure.

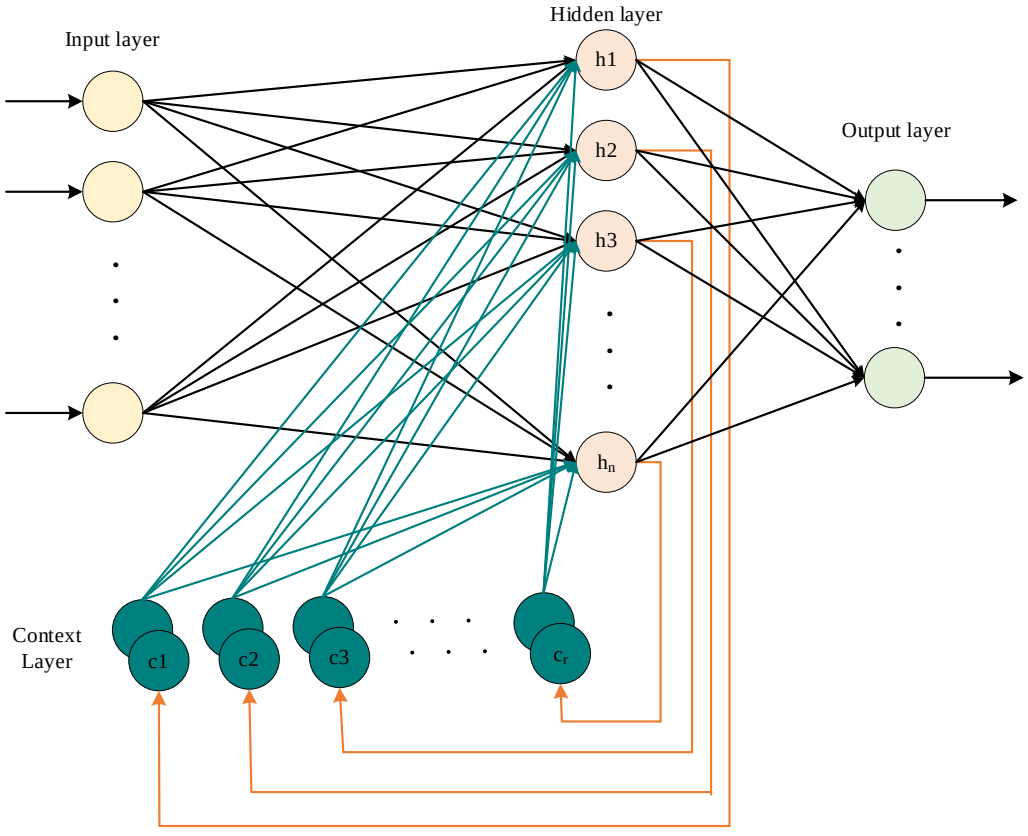

Figure 1: Schematic diagram of Elman network structure

The core principle of the Elman network is as follows. First, the output vector $y(t)$ of the network is obtained from the output vector $h(t)$ of the implicit layer through the nonlinear transformation function $g(*)$of the output layer with the expression (1):

$$y(t) = g(w_{hy}w_{cj}^{y}h(t)) \quad (1)$$

w_{hy} denotes the weight matrix between the hidden and output layers. Secondly, the output $h(t)$ of the implicit layer is obtained from the current input $v(t-1)$ and the output $c(t)$ of the context layer through the

nonlinear transformation function $f(*)$ of the implicit layer with the expression (2):

$$h(t) = f(w_{xh}v(t-1) + w_{ch}c(t)) \quad (2)$$

w_{xh} refers to the weight matrix from the input to the hidden layer. w_{ch} denotes the weight matrix from the takeover layer to the hidden layer. Finally, the output $c(t)$ of the take-on layer is the output $h(t-1)$ of the implicit layer at the previous time step, that is (3):

$$c(t) = h(t-1) \quad (3)$$

This structure allows the Elman network to capture the temporal dynamics of the input data. For construction cost estimation, it means that the network can consider the impact of historical cost data on current cost estimates, thus improving the accuracy of the predictions.

Furthermore, the computational flow of the Elman network is suggested in Figure 2.

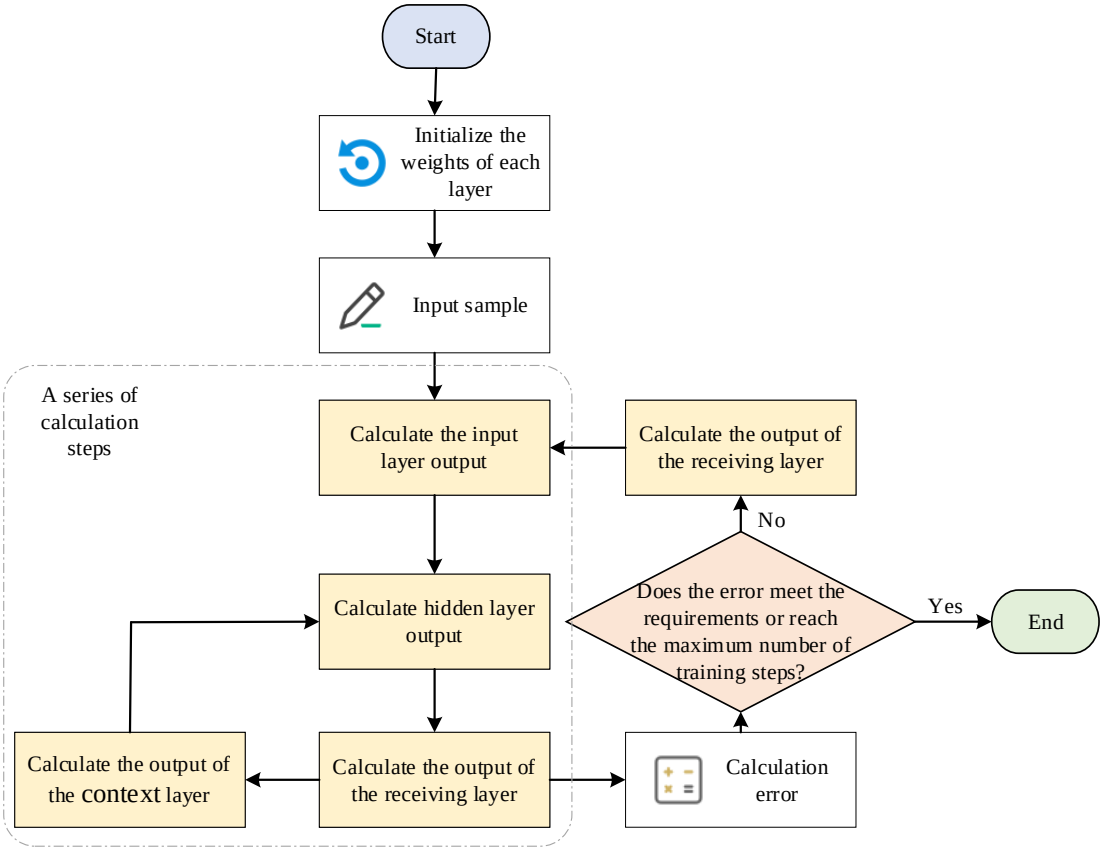

Figure 2: Elman network computational flow

In Figure 2, the network initializes the weights of each layer as a necessary preparation before training starts. The initial setup of these weights significantly impacts the learning effectiveness and overall performance of the network. Network learning is then built on the input samples, which include past construction project cost data and other pertinent features. The outputs of the input, hidden, and output layers are then computed sequentially. Meanwhile, after obtaining the output of the hidden layer, the output of the context layer is further computed. In this step, the current output of the hidden layer is used as the input for the context layer in the next time step. This step is the key to the short-term memory mechanism of the Elman network, allowing it to retain information from previous states while processing sequential data. The output layer error is determined by comparing the actual cost data with the network's predicted outputs, following the computation of outputs across all layers. A critical element of supervised learning, this error computation (denoted as *E*) provides the network with feedback for adjusting its parameters. Lastly, the error *E* is utilized to check if the maximum number of training steps has been completed or if the predefined requirements are met. If the error *E* does not decrease sufficiently, the training cycle continues, with the weights being adjusted to reduce the prediction error. This process is repeated until the network performs adequately or the training reaches the set number of iterations.

In the above step, the error *E* is used to measure the difference between the predicted output of the network, $y(t)$, and the desired output as $\hat{y}(t)$, calculated as (4):

$$E = \frac{1}{2}\left(y(t) - \check{y}(t)\right)^T (y(t) - \hat{y}(t)) \quad (4)$$

To adjust the weights, the partial derivatives of the error *E* with respect to the weights need to be calculated. The partial derivatives of the weights w_{ji}^{y} for the output layer are (5):

$$\frac{\partial E}{\partial w_{ji}^{y}} = -\left(\hat{y}_{d,i}(t) - y(t)\right)\frac{\partial y_i(t)}{\partial w_{ji}^{y}} = -(\hat{y}_{d,i}(t) - y(t)g'_j(*)x_i(t)) \quad (5)$$

w_{ji}^{y} y refers to the weight connecting the *i*th input unit and the *j*th output unit; $g'_j(*)$ represents the derivative of the activation function of the output layer; $x_i(t)$ denotes the output of the *i*th input unit at time *t*. Let $\varphi_j^0 = (\hat{y}_{d,i}(t) - y(t)g'_j(*)$, so (6):

$$\frac{\partial E}{\partial w_{ji}^{y}} = -\varphi_j^0 x_i(t), i = 1,2,\cdots,m; j = 1,2,\cdots,n \quad (6)$$

m is the number of neurons in the input layer and n is the number of neurons in the hidden layer.

Taking E as the partial derivative of the input layer weight w_{ji}^{x}, it can get (7):

$$\frac{\partial E}{\partial w_{ji}^{x}} = \frac{\partial E}{\partial x_i(t)} \frac{\partial x_i(t)}{\partial w_{ji}^{x}} = \sum_{i=1}^{m} (-\varphi_j^0 w_{ji}^{x}) f'_i(*) v_q(t-1) \quad (7)$$

$f'_i(*)$ denotes the derivative of the hidden layer activation function. Let $\varphi_j^h = \sum_{i=1}^{m} (-\varphi_j^0 w_{ji}^{x}) f'_i(*)$ L, then get (8):

$$\frac{\partial E}{\partial w_{ji}^{x}} = -\varphi_j^h v_q(t-1), i = 1,2,\cdots,m; j = 1,2,\cdots,n; q = 1,2,\cdots,r \quad (8)$$

r is the number of neurons in the splice layer.

The partial derivative of the connection weight w_{jl}^{c} is obtained (9):

$$\frac{\partial E}{\partial w_{jl}^{c}} = \sum_{i=1}^{m} (-\varphi_j^0 w_{ji}^{x}) \frac{\partial x_i(t)}{\partial w_{jl}^{c}}, l = 1,2,\cdots,n; j = 1,2,\cdots,n \quad (9)$$

According to the chain rule (10):

$$\frac{\partial x_j(t)}{\partial w_{jl}^{c}} = \frac{\partial}{\partial w_{jl}^{c}} f_j\left(\sum_{i=1}^{n} w_{ji}^{c} x_{c,i}(t) + \sum_{i=1}^{r} w_{jl}^{x} v_i(t-1)\right) = f'_j(*) x_{c,i}(t) + \sum w_{ji}^{y} \frac{\partial x_{c,i}(t)}{\partial w_{jl}^{y}} \quad (10)$$

The dependence of $x_c(t)$ on the connection weight w_{ji}^{y} is ignored, and the following results are obtained (11) and (12):

$$\frac{\partial x_j(t)}{\partial w_{jl}^{x}} = f'_j(*) x_{c,l}(t) \quad (11)$$

$$f'_j(*) x_{c,l}(t) = f'_j(*) x_l(t-1) + \alpha * f'_j(*) x_{c,l}(t) \quad (12)$$

α refers to the forgetting factor. By substituting equation (12) into equation (11), it can obtain (13):

$$\frac{\partial x_j(t)}{\partial w_{jl}^{y}} = f'_j(*) x_l(t-1) + \alpha * \frac{\partial x_j(t-1)}{\partial w_{jl}^{y}} \quad (13)$$

Elman's equation (14)-(18) is derived from $\Delta W = -\eta \frac{\partial E}{\partial W}$:

$$\Delta w_{ji}^{y} = \eta \varphi_j^0 x_j(t), i = 1,2,\cdots,m; j = 1,2,\cdots,n \quad (14)$$

$$\Delta w_{jq}^{c} = \eta \varphi_j^h v_q(t-1), j = 1,2,\cdots,n; q = 1,2,\cdots,r \quad (15)$$

$$\Delta w_{jl}^{x} = \eta \sum_{i=1}^{m} (\varphi_j^0 w_{ji}^{x}) \frac{\partial x_j(t)}{\partial w_{jl}^{x}} \varphi_j^0 x_j(t), j = 1,2,\cdots,n; l = 1,2,\cdots,n \quad (16)$$

η is the learning rate. Meanwhile,

$$\varphi_j^0 = (\hat{y}_{d,i}(t) - y(t) g'_j(*) \quad (17)$$

$$\varphi_j^h = \sum_{i=1}^{m} (-\varphi_j^0 w_{ji}^{x}) f'_i(*) \quad (18)$$

Through this calculation process, the Elman network can gradually learn the complex relationship between building cost data and complete cost prediction. This dynamic learning and forecasting mechanism makes the Elman network perform well in dealing with time series forecasting problems such as construction cost estimation. The pseudocode for the Elman model is illustrated in Figure 3.

```
Algorithm: Elman Neural Network

Input:
  - Training data
  - Learning rate
  - Maximum iterations

Initialization:
  - Randomly initialize weights
  - Set initial context layer to zero

Training:
Repeat until convergence or maximum iterations:
  1. Compute hidden layer output
  2. Update context layer
  3. Compute network output
  4. Calculate error
  5. Backpropagate and update weights

Prediction:
For each input in test data:
  1. Compute hidden layer output
  2. Update context layer
  3. Compute final output
```

Figure 3: The pseudocode for the Elman model

3.3 Optimization of the Elman model based on GA

Although the Elman neural network has remarkable advantages in processing time series data, its performance is highly dependent on the initial weight settings and the choice of network structure. In addition, the Elman network is easily affected by local minimum, which can lead to suboptimal solutions and negatively impact prediction accuracy and generalization ability [23]. To overcome these limitations, GA is introduced to optimize the Elman model. Darwin's theory of natural selection and the global search principle of biogenetics serve as the foundation for GA, an optimization algorithm designed to mimic the natural evolution process. Biological evolution mechanisms, including natural selection, genetic variation, and crossover, are simulated by GA, which is extensively used to tackle complicated combinatorial optimization problems by gradually improving the quality of solutions. GA has strong global search ability and adaptability, and can effectively deal with optimization problems under high dimensional, nonlinear, and complex constraints [24]. The basic idea of GA is to simulate natural selection and genetic mechanisms by operating a population composed of multiple individuals to produce better solutions. Although GA possesses global search capabilities and strong adaptability, there are certain limitations in its optimization process. GA may encounter issues of high computational complexity and time costs when dealing with large-scale datasets. Additionally, the

convergence speed of GA can be slow, especially in large search spaces, where there is a risk of premature convergence or falling into local optimal solutions [25]. The implementation steps of GA are displayed in Figure 4.

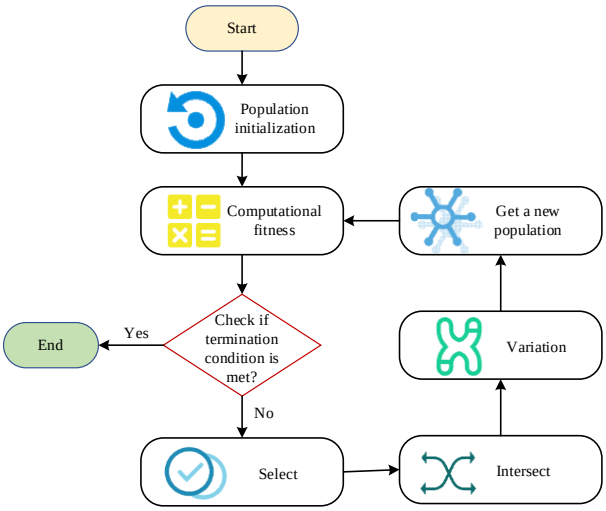

Figure 4: GA implementation process

This study uses the GA to optimize the adjustment of Elman network weights and thresholds, and the specific steps are as follows [26, 27].

(1) Population initialization. Several initial individuals are randomly generated in the solution space, and each individual corresponds to a set of potential Elman network weights and thresholds. Each individual can be regarded as the coding form of Elman network parameters (real number coding), including the connection weights between input and hidden layers, hidden and output layers, and the threshold of each neuron.

(2) Fitness calculation. According to the performance index of the Elman network (for example, the mean square error of construction cost estimation), the fitness of each individual is evaluated. The network corresponding to the individual performs better on a given task the higher the fitness.

(3) Selection of the operation. Using probability techniques like roulette wheel selection, the fittest members of the current population are chosen to go into the next generation based on their fitness values. This step imitates the natural selection process of "survival of the fittest" in biology.

(4) Cross operation. Individuals are randomly paired from the selected ones and undergo a single-point crossover operation according to a set crossover probability (0.6). This involves randomly selecting a position in the chromosome and exchanging the gene segments before and after that position, generating new combinations of weights and thresholds. This method improves search efficiency by exploring different parameter combinations.

(5) Mutation operation. A small probability (0.2) is used to randomly mutate certain genes of the selected individuals. The specific method is to add a random disturbance that follows a normal distribution (e.g., with a mean of 0 and a standard deviation of 0.1) to the original weights or thresholds. Thus, it can increase the diversity of the population and avoid local optimal solutions.

(6) Termination conditions. For one thing, the algorithm automatically stops when it reaches the preset maximum number of iterations (200 times). For another, if the optimal fitness value of the population does not improve by more than a predetermined threshold (0.001) over a continuous number of generations (20), it is considered that the algorithm has converged. In addition, the optimization process is terminated early. By introducing these clear stopping criteria, the stability of the optimization process can be effectively ensured, while also enhancing the applicability and reliability of the algorithm in practical problems.

Through the aforementioned optimization process, GA can effectively adjust the weights and thresholds of the Elman network, improving the model's generalization ability and prediction accuracy. The rationality of parameter settings is determined through multiple experimental tests. Meanwhile, the specific implementation of crossover and mutation ensures a high degree of repeatability in the study, providing an effective modeling tool for complex construction cost estimation tasks.

Figure 5 shows the calculation flow of the finally formed GA-Elman model based on GA.

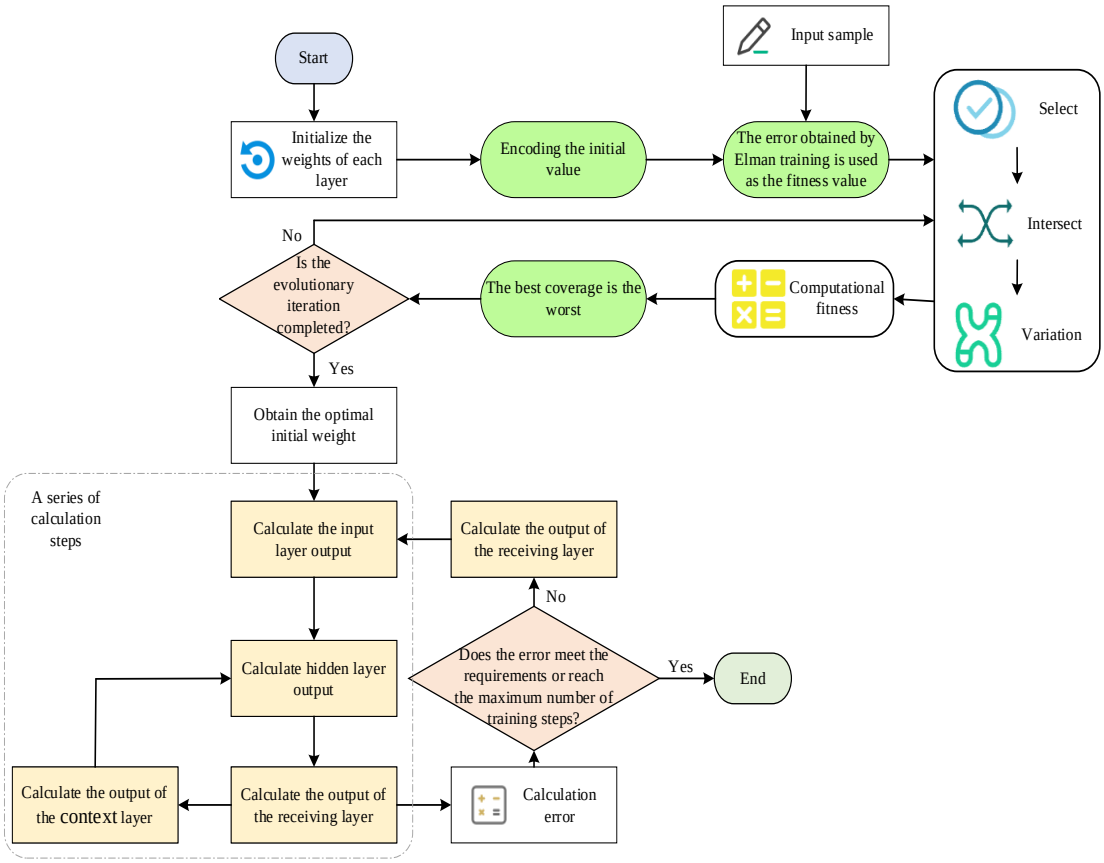

Figure 5: Calculation flow of GA-Elman model

The GA optimization of the Elman neural network can reduce the probability of the model reaching local optima, and enhance the network's global search ability. Meanwhile, it can accelerate the convergence speed of the training process and improve the model's prediction accuracy. This is especially important for complex construction cost estimation tasks. Especially when faced with time-related data, the optimized GA-Elman network can better capture the dynamic characteristics of data and realize more accurate cost estimation and risk prediction.

3.4 Application of cost estimation model in overspending risk

In the cost management of construction projects, the assessment and control of overspending risk is a crucial link. The assessment of overspending risk relies on the accuracy of cost estimation while requiring scientific quantification of risk factors and their weights. The GA-Elman model can accurately capture the time series characteristics of cost data through dynamic memory mechanisms, offering vital support for the quantitative assessment of overspending risk. Firstly, the assessment of overspending risk is based on the cost deviation rate p, and the degree of risk is quantified by the deviation between the model's predicted value c' and the actual cost value c. The specific calculation reads (19):

$$p = \frac{|c-c\prime|}{c\prime} \times 100\% \quad (19)$$

In this context, the higher the deviation rate, the greater the overspending risk. Based on this deviation rate, the risk can be classified into three levels: low, medium, and high, providing decision-makers with a more intuitive risk assessment index.

Furthermore, the model quantifies the key risk factors through a comprehensive index system. The index system designed in this study encompasses four major dimensions: architectural features, structural features, project positioning, and project environment. Within each dimension, specific indexes are assigned different weights to reflect their relative importance in contributing to cost overruns. For instance, in the architectural features dimension, the "number of floors" and "building area" directly influence material and labor costs, with their weights determined by principal component analysis. In contrast, in the project environment dimension, "management level" and "technical personnel level" are quantified using fuzzy comprehensive evaluation methods. The distribution of risk factor weights follows (20):

$$w_i = \frac{v_i}{v} \quad (20)$$

w_i represents the weight of the ith risk factor, with a value range of 0 to 1 and a total weight of 1; v_i refers to the contribution of the ith index to the total deviation; v denotes the total deviation. The GA-Elman model can identify and predict the primary risk factors leading to overspending through historical data. For example, the model can use retrospective analysis to determine that material price fluctuations contribute 35% to cost deviations, construction delays account for 25%, design changes contribute 20%, and other factors make up 20%. This detailed quantitative analysis helps managers pinpoint key risk sources and provides data support for formulating targeted risk control strategies.

Additionally, the GA-Elman model simulates the impact of different cost control strategies on overspending risk. For instance, in the case of significant material price fluctuations, the model can simulate cost trends for diverse procurement strategies (such as bulk purchasing in advance or phased procurement) and assess the mitigation effects of each strategy on overspending risk. This data-driven simulation analysis offers project managers a scientific decision-making tool.

To sum up, the GA-Elman model in overspending evaluation provides intuitive risk levels through the quantification of cost deviations. Meanwhile, it offers a systematic approach to risk identification, assessment, and control through the weight allocation to key risk factors and simulation analysis. By applying this model in-depth, project managers can remarkably improve risk management efficiency, reduce economic losses caused by overspending, and ultimately enhance the construction projects' cost-effectiveness and success rate.

4 Model Performance verification

4.1 Data source and experimental design

To ensure the universality and representativeness of the experiment, data are collected from multiple sources, ensuring the diversity and reliability of the data. The social and economic development level of each region and the number of prefabricated buildings built are comprehensively considered. The basic data are obtained from professional platforms such as the China Prefabricated Building Market Analysis Report, Prefabricated Building Network, and Zhongce Big Data Website. Additionally, data from 45 groups of prefabricated building projects in cities such as Beijing, Tianjin, Hebei, and Shenyang over the past four years are collected. These data cover many dimensions, such as architectural features, structural features, project positioning, and project environment, offering rich information for model training and testing. Taking the indexes A1-A3 of architectural features as an example, the variance analysis of these data is detailed in Table 4.

Table 4: Variance analysis of architectural feature indexes

Difference source	Sum of Squares	Degrees of Freedom	Mean Square	F	P-value	F crit
Row	3,417,030,830	44	77,659,791	1.000	0.488	1.515
Column	4,022,937,273	2	2,011,468,636	25.902	0.000	3.100
Error	6,833,762,444	88	77,656,391			

Table 4 shows significant mean differences (P<0.05) among variables A1, A2, and A3, while the differences between samples are not significant. This indicates that different samples have a relatively small impact on the results of variance analysis. These data can more comprehensively illustrate the distribution characteristics of architectural feature data, providing data support for model prediction. To enhance the model's generalization ability, the gathered data are normalized to remove the impact of varying dimensions and ordering. Specifically, the Min-Max normalization method is adopted to map the data values of each index to the interval [0, 1], and the normalization equation is as follows (21):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{21}$$

X is the original data; X_{min} and X_{max} are the minimum and maximum values of the index, respectively. Through this method, the differences in dimensions and magnitudes between different indicators have been eliminated, ensuring the stability and accuracy of the model during training and testing. The training set comprises 36 sets of data; The test set contains 9 sets of data, which are randomly selected from the dataset and arranged in a 4:1 ratio. Furthermore, to comprehensively evaluate the performance and reliability of the model, this study further adopts the k-fold cross-validation technique (k=5) based on the division of training and testing data. By partitioning the dataset k times to ensure that each subset participates in training and validation, the potential random errors caused by a single partition are effectively reduced. In addition, the stability and credibility of the model evaluation results are improved. The experimental setup and parameter values are shown in Table 5.

Table 5: Experimental environment and parameter setting

Hardware/parameter name	Parameter/value
Operating system	Windows10
CPU	AMD R7-5800H
Basic frequency	3.2 GHz
Display card	RTX3060
Memory	16 GB
Hard disc	512 G SSD
Input layer node	15
Output layer node	1
Hidden layer node	10
Maximum number of iterations	200
Error tolerance	1×10^{-5}
Evolutionary algebra	20
Population size	10
Cross probability	0.6
Mutation probability	0.2

Relative Error (RE) and Mean Absolute Percentage Error (MAPE) are used as evaluation indexes to evaluate the accuracy of prediction results. The calculation equations of them are (22) and (23):

$$\mathrm{RE} = \frac{y'_i - y_i}{y'_i} * 100\% \tag{22}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{n} \frac{|y_i - y'_i|}{y_i} \tag{23}$$

N represents the number of samples. y_i and y'_i refer to the predicted and actual values. In the cost estimation model, REP measures the difference between the predicted and actual costs to evaluate the model's prediction performance. MAPE index can directly reflect the RE between the actual and predicted values of the model, and it is an important index to measure the model's prediction performance.

4.2 Test results of the GA-Elman model

Firstly, the GA-Elman model is trained, and its training result in the training set is presented in Figure 6.

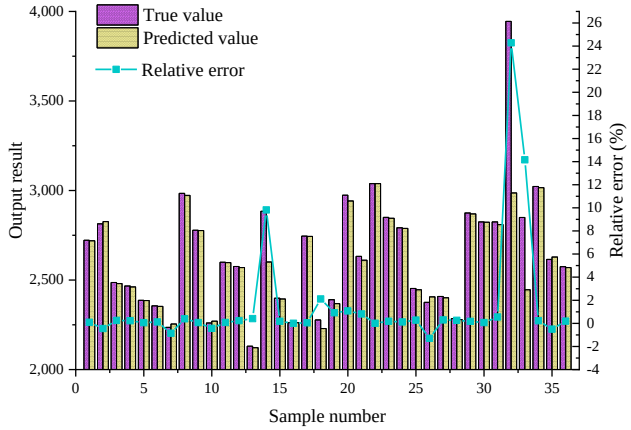

Figure 6: Training results of the GA-Elman model in the training set

Results in Figure 6 demonstrate that the GA-Elman model has good prediction accuracy. This is because the predicted values for most samples are extremely close to the true values and the RE percentage is typically less than 1%. However, there are also some samples with large prediction errors, such as Samples 14 and 32, with RE percentages as high as 9.816% and 24.284%. The reasons for these issues may be attributed to several factors. Firstly, the data characteristics of these samples may significantly deviate from the overall distribution of the training set, such as abnormal fluctuations in key factors like material prices, construction conditions, or design complexity. For instance, Sample 32 may have actual costs that far exceed the model's predictions due to the use of certain specific processes or unexpected construction delays. Secondly, the model may exhibit limitations in handling rare features in small samples, especially when these features are not adequately represented in the training data, making it difficult for the model to capture their nonlinear relationships. Additionally, the data preprocessing process may not have eliminated the effects of noise or outliers, which could also amplify errors. To address the aforementioned issues, the following approaches can be taken. Firstly, it is necessary to optimize data preprocessing methods by employing techniques such as denoising and smoothing to improve data quality. Meanwhile, the detection and handling of outliers are strengthened to reduce the noise interference on the model. Secondly, the sample diversity of the training dataset is expanded, particularly for samples with rare or abnormal features, by increasing the proportion of related data, thereby enhancing the model's ability to learn nonlinear relationships. Moreover, integrating learning methods or hybrid model structures can be introduced to combine the advantages of multiple algorithms and improve the model's generalization ability. Lastly, for key features such as material prices and construction conditions, targeted feature engineering strategies can be designed to ensure that the model can more accurately capture their impacts, thus reducing the occurrence of extreme errors.

Taking the Elman network, RNN, and SVR as the benchmark model, the test set is tested on the GA-Elman and benchmark models, respectively, and the results are revealed in Figure 7.

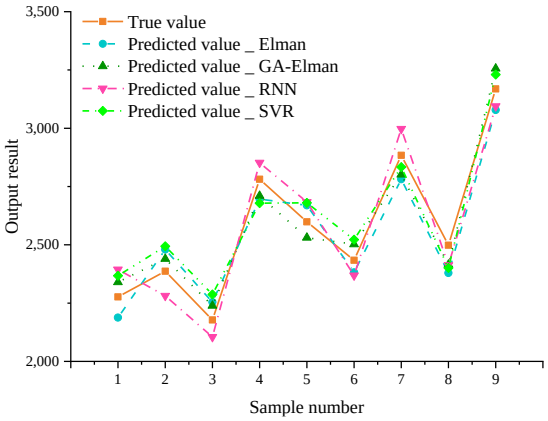

Figure 7: Comparison between the GA-Elman model and benchmark model

On most test samples, the predicted value of the GA-Elman model in Figure 7 is more similar to the true value. The maximum differences between the predicted and actual results for the Elman network, RNN, and SVR are 118.99, 117.65, and 102.94, respectively. The GA-Elman model's maximum difference between the predicted and true values is 87.21. These results show that the GA-Elman model optimized by GA has higher prediction accuracy and robustness in construction cost estimation, thus verifying the effectiveness of GA in neural network weight optimization.

4.3 Comparison of cost estimation results before and after Elman model optimization

To further compare the cost estimation results before and after the optimization of the Elman model, the difference between the predicted and true value and the RE of the four models are calculated, as denoted in Figure 8.

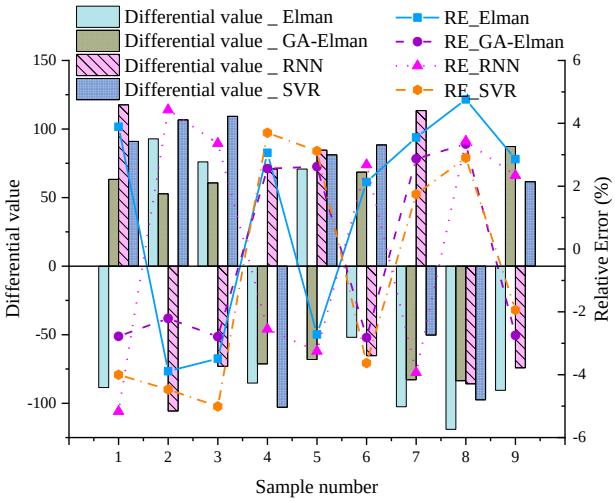

Figure 8: Analysis of cost prediction results of four models

In Figure 8, the differences and REs of the GA-Elman model across all test samples are generally lower than those of the Elman model. The mean absolute difference between the predicted and actual values for the GA-Elman model is 70.93, while for the Elman network, RNN, and SVR, they are 86.38, 87.83, and 87.63, respectively. In some samples, the GA-Elman model still exhibits relatively large errors. The main reasons for these larger errors are twofold. First, data irregularity. For instance, Sample 8 may have been affected by drastic fluctuations in material prices or abnormal construction environments, leading to actual costs significantly higher than the model's predictions. However, these exceptional situations are not adequately represented in the training data. Second, model limitations. The GA-Elman model has enhanced its ability to capture nonlinear features through parameter optimization by GA. Nevertheless, it may still be insufficiently responsive to the dynamic changes of certain key influencing factors, such as unexpected design changes or construction delays. Meanwhile, the calculated MAPE for the GA-Elman model is 2.75%, which is significantly reduced compared to the Elman model's 3.37%. The MAPEs for RNN and SVR are 3.46% and 3.45%, respectively, higher than that of the GA-Elman model. This further demonstrates the effectiveness of GA in optimizing neural network parameters and improving prediction accuracy. These results show that GA-Elman model is more accurate in capturing the complex relationship of construction cost data, thus providing more reliable support in cost estimation and overspending risk assessment of construction projects.

In addition, the training time of the GA-Elman and Elman models is compared, and the results are listed in Table 6.

Table 6: Comparison of training time between GA-Elman and Elman models

Model	Training dataset size (number of samples)	Training time (seconds)
Elman model	100	12.36
	500	56.47
	1,000	115.82
GA-Elman model	100	18.75
	500	72.93
	1,000	142.68

Table 6 indicates that the training time of the GA-Elman model is slightly higher than that of the traditional Elman model, primarily due to the additional optimization step introduced by the GA. However, this extra computational cost is justified, as the GA-Elman model optimizes the network's initial parameters and weights through GA, significantly improving both prediction accuracy and generalization ability. Specifically, when the sample size is small (e.g., 100 samples), the training time of the GA-Elman model is 18.75 seconds, only 6.39 seconds longer than the Elman model. When the sample size increases to 1,000, the training time becomes 142.68 seconds, which is 26.86 seconds longer than the Elman model. This increase in training time is acceptable in light of the improvements in prediction performance.

From both a construction and economic perspective, the improvements made by the GA-Elman model are significant. In construction management, accurate cost forecasting is crucial for budget control and risk mitigation. The GA-Elman model's high prediction accuracy (with a MAPE of only 2.75%) enables it to capture the complex nonlinear relationships in construction costs, thus providing project managers with more reliable decision support. This capability is especially beneficial for large and complex projects, as it helps reduce overspending risks and delays due to budget miscalculations. Additionally, by accurately assessing key influencing factors (such as material prices and construction conditions), the model helps managers identify potential risks earlier, allowing for timely adjustments in construction plans and financial allocations.

From an economic perspective, the application of the GA-Elman model in budget optimization remarkably improves resource allocation efficiency. Compared to the traditional Elman model and other benchmark models, the GA-Elman model offers a clear advantage in effectively reducing unnecessary financial waste and optimizing financial planning. For example, for cost-sensitive samples (such as Samples 14 and 32), there is still some error. However, the model provides managers with a cost estimate closer to the actual values, laying a foundation for reasonable financial resource distribution and cash flow control. Moreover, the GA-Elman model's ability to identify and quantify overspending risk allows enterprises

to develop more scientifically-based long-term financial strategies, thereby reducing the economic losses caused by uncontrollable costs.

In conclusion, the GA-Elman model has considerable potential in construction cost estimation and economic risk management. It enhances the intelligence level of construction management while providing a reliable tool for budget optimization and cost control. The model contributes positively to lean management and improved economic efficiency in the construction industry.

4.4 Discussion

Compared to the existing models summarized in Table 1, the proposed GA-Elman model demonstrates significant advantages in construction cost estimation and overspending risk assessment. In contrast to models such as GPR and XGBoost, the GA-Elman model is better suited for handling dynamic changes in time series data. For instance, while GPR exhibits high accuracy in predicting tunnel geological conditions, its sensitivity to data scale can lead to decreased computational efficiency when dealing with large-scale complex construction projects. In comparison, the GA-Elman model, by optimizing weights and thresholds through GA, can process large-scale data more efficiently while fully capturing dynamic changes, thus enhancing the model's applicability.

The comparison with ANNs and gradient boosting models indicates that although these models perform well in rapid construction cost estimation, they lack capability in risk assessment. For example, the gradient boosting model primarily focuses on cost optimization and cannot effectively identify key risk factors leading to overspending. In contrast, the GA-Elman model can predict costs and identify key drivers of overspending risks (such as fluctuations in material prices and construction delays) through its dynamic memory mechanism. As a result, it can provide project managers with more targeted decision support.

Compared to hybrid models such as ANN combined with the Grasshopper algorithm and ARIMA-ANN models, the GA-Elman model performs better in long-term forecasting and modeling complex data relationships. Although the ARIMA-ANN model has certain advantages in long-term construction cost estimation, its ability to capture nonlinear features is limited. The GA-Elman model, by optimizing network structure through the global search capability of GA, can better model nonlinear and temporal characteristics. Meanwhile, it can achieve superior prediction accuracy in practical tests, with the MAPE reduced to 2.75%.

In summary, the GA-Elman model outperforms existing models in terms of cost prediction accuracy, overspending risk assessment ability, and adaptability to complex data. Thus, it offers an innovative solution for construction cost management and significant practical guidance for budget control and risk management in complex engineering projects.

5 Conclusion

This study analyzes the application of the GA-Elman model in construction cost estimation and overspending risk analysis by constructing a construction cost estimation model based on the Elman network and optimizing the model with GA. It verifies the performance of the model through experiments. The conclusions are as follows. (1) The GA-Elman model's high prediction accuracy is demonstrated by the fact that, on the training set, the predicted value on most samples is very near to the true value and the RE percentage is typically within 1%. (2) When compared to the Elman network, the GA-Elman model's projected value is closer to the actual value, and on all test samples, the model's difference and RE are typically smaller than those of the Elman model. (3) The GA-Elman model's MAPE is 2.75%, a considerable decrease from the Elman model's 3.37%. It further proves the effectiveness of GA in optimizing neural network parameters and improving prediction accuracy. In short, by optimizing GA, the GA-Elman model increases the ability to detect possible overspending, which is crucial for efficient cost control and budget management, in addition to improving the accuracy of cost prediction. Although this study has made some progress in construction cost estimation and overspending risk assessment, there are still some limitations. First, the robustness of the model needs to be enhanced, as extreme errors occurring on specific data samples indicate insufficient stability. Second, the study only selects certain regions and prefabricated buildings, and the limitation of the sample range may affect the model's generalization ability, making it difficult to apply to other regions or different building types. Additionally, there may be biases in data selection, such as differences between urban and rural projects or the impact of various construction technologies (e.g., traditional construction versus modern building technologies). These factors could significantly affect the model's applicability and accuracy. Future research should consider more comprehensive data collection, covering a wider range of regions, building types, and different construction technologies, to avoid biases caused by data limitations, thereby enhancing the model's generalization ability and adaptability. At the same time, more advanced data preprocessing techniques and algorithm optimization methods can be explored to improve the model's prediction accuracy and stability, providing stronger support for widespread application.

Funding

This work was supported by Key Laboratory of Building Structures in Anhui Universities (Anhui Xinhua University) 2023 school-level scientific research project: “Application Research of BIM Technology in Cost Management of Engineering Construction Projects” (Project batch number: KLBSZD202301, Host: Wu Qian).

Conflict of interest statement

There is no conflict of interest in this study.

Ethical compliance statement

This study does not involve experiments on humans or animals and does not require ethical approval.

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Comparison of Machine Learning Algorithms for Predicting Thyroid Disorders in Diabetic Patients

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Keywords: machine learning, classification, decision tree, random forest, support vector machine, naïve bayes, logistic regression, K-nearest neighbor, diabetes, thyroid disorders

Received: August 17, 2024

Machine Learning (ML), a subfield of Artificial Intelligence (AI), has been used successfully in the healthcare domain for disease diagnosis. Thyroid disorders and diabetes are two of the most prevalent and interconnected chronic diseases, as both play critical roles in regulating various physiological processes in the body. This study aims to predict thyroid disorders in diabetes patients using six machine learning algorithms: Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Naïve Bayes (NB), and Support Vector Machine (SVM). A locally sourced dataset comprising 44,539 instances of diabetic patients was utilized, undergoing preprocessing steps including data cleaning, encoding, and balancing. Two balancing techniques were employed: manual balancing and RandomUnderSampler. The dataset was partitioned into training and testing sets using a Stratified K-Fold cross-validation approach with 10 folds to ensure robust evaluation. Each algorithm's performance was assessed using metrics such as accuracy and F1-score. Among the models, the RF algorithm outperformed the others, achieving the highest accuracy of 95% on the manually balanced dataset and 84% when the RandomUnderSampler technique was employed. Additionally, the F1-scores for RF were 95% and 82%, respectively, indicating its robustness in handling imbalanced datasets. This study highlights the importance of selecting appropriate preprocessing techniques and machine learning methods for healthcare datasets. The findings can assist healthcare providers in making early diagnoses and interventions for thyroid disorders in diabetic patients, potentially improving their quality of life and overall healthcare outcomes.

Povzetek: Opisana je uporaba strojnega učenja za napovedovanje motenj ščitnice pri bolnikih s sladkorno boleznijo. Algoritem naključnih gozdov doseže najvišjo točnost in oceno F1 na uravnoteženem naboru podatkov.

1 Introduction

Diabetes and thyroid disorders are among the most prevalent chronic diseases affecting the endocrine and metabolic systems [1]. These two diseases are often coexisted and strongly linked together, as many studies have shown that there is a higher prevalence of thyroid disorders in diabetic patients and vice versa [2].

Diabetes is a chronic condition that is caused by elevated levels of blood sugar (glucose) [3]. This occurs when the body either cannot use the insulin it produces effectively or cannot produce enough insulin. Insulin is a hormone that allows the body cells to absorb and use glucose for energy and helps regulate blood sugar [4]. As a result, diabetes affects various body functions. There are four types of this disease

- Type 1 diabetes is an autoimmune disease which is usually diagnosed in children and young adults [5], it occurs when the insulin-producing cells of the
- pancreas is attacked by the immune system which leads to little or no insulin [6].
- Type 2 diabetes is the most common type of diabetes that often occurs in older adults when the body doesn't produce enough insulin or becomes resistant to insulin [6].
- Gestational diabetes this type develops as a complication in women during pregnancy and usually goes away after the baby is born [7].
- There are fewer common types of diabetes that are caused by genetic conditions and diseases such as secondary diabetes and monogenic diabetes.

Thyroid disorder is a disease that affects the function of the thyroid gland in producing the appropriate amounts of thyroid hormones T3 (tri-iodothyronine), and T4(tetra-iodothyronine), as these hormones play an important role in controlling many vital activities of the body such as heart rate, energy level, metabolism, bone health, and many other functions. The most common thyroid disorders are Hyperthyroidism and Hypothyroidism [8]. In hyperthyroidism, the thyroid gland overproduces thyroid hormones. While in hypothyroidism the thyroid gland does not produce enough thyroid hormones [8].

Studies show that there is a higher prevalence of thyroid disorders among patients with type 1 or type 2 diabetes in comparison to non-diabetic patients, which reveals their close relationships, it also shows that autoimmunity is a key to understanding the link between type 1 diabetes and autoimmune thyroid disorders [9].

The presence of insulin resistance or diabetes increases an individual's risk of developing thyroid disorders while having thyroid disorder can increase the risk of developing diabetes and metabolic syndrome [10]. It is very important to diagnose thyroid disorder in diabetic patients and a routine screening should also be recommended. It is necessary that the clinician identify the high-risk diabetic groups and manage the thyroid abnormalities if present as soon as possible to reduce the risk of further complications [10].

The primary aim of this study is to assess the effectiveness of six machine learning methods (Decision tree, random forest, Support Vector Machine, Naïve Bayes, k nearest neighbor, logistic regression) in predicting the presence or absence of thyroid disorders in diabetes patients. By comparing the results of each method, we aim to identify the most accurate model to enhance early detection and intervention. Machine learning methods used in this study differ in their nature and work but they are all used for predicting new states.

Logistic regression (LR): is a classification machine learning algorithm that is used for predictive analysis based on the concept of probability [11]. LR classifies the data using the logistic sigmoid function. LR predicts one of two possible outcomes of a categorical dependent variable. Therefore, the outcome must be a categorical or discrete value. It does not give the value of either True or False, Yes or No, 0 or 1, etc. instead, it gives a probabilistic value between 0 and 1[12]. To classify instances into the two classes. a common approach is to use a threshold value (e.g., 0.5), If the predicted probability is above the threshold, the instance is assigned to one class, and if it is below the threshold, then it is assigned to the other class. LR is widely used for many tasks such as fraud detection, disease diagnosis, and prediction, Tumor Malignant or Benign, mail spam or not spam, etc. [11].

Naïve Bayes (NB): is a simple machine learning classification algorithm based on Bayes' Theorem [13]. It is called naïve because of the assumption of conditional independence among the features which means that the presence or absence of one feature in a class is independent of the presence or absence of the other features. It is used for a large amount of data. Bayes' theorem, Rule, or law is used to describe the probability of a hypothesis with existing knowledge. Bayes' theorem formula is [11]:

$$\mathbf{P}(\mathbf{A}|\mathbf{B}) = (\mathbf{P}(\mathbf{B}|\mathbf{A}) * \mathbf{P}(\mathbf{A})) / \mathbf{P}(\mathbf{B}) \quad (1)$$

NB is computationally efficient, easy to create, and can handle large datasets [12]. It is very effective in text classification tasks, such as spam filtering. Despite that it's a simple algorithm with the independence assumption, it can often outperform complex algorithms.

Decision Tree (DT): is one of the supervised Machine learning algorithms that is used for both classification and regression problems [14]. DT is a visual representation of the decision-making process, it's a tree-like graph that partitions the data based on the input features, the tree starts with a root which has the highest gain then nodes and branches. Where each node represents a test that follows the if-then statement and leads to a different branch, each branch leads to one outcome (decision) [15]. It is a widely used algorithm for predicting diseases.

K-Nearest Neighbors (KNN) is one of the simplest lazy learning machine learning algorithms that make predictions based on the entire data [12],[16]. The algorithm is used for solving classification and regression tasks. KNN assumes that similar data points are located near each other, the similarity is called distance. It uses distant measures like Euclidean to measure similarity. Although KNN is a very simple and easy-to-implement algorithm, its results can be very competitive [16].

Support Vector Machine (SVM) is one of the most popular machine learning algorithms. It is used primarily for classification tasks but can also be used for regression [12]. The main goal of SVM is to separate the data with a hyperplane into different classes so that we can easily put the new data point into one of the classes [11]. SVM can be effective in high-dimensional spaces and is widely used in image classification, Face detection, text categorization, and handwriting recognition.

Random Forest (RF) is a machine learning algorithm that belongs to the group of decision-tree-based methods [13]. It can be used for classification tasks and regression. Random forest is a collection of decision trees built during the training process and then the prediction of these trees is combined during the testing process. RF approach gives a better accurate result in comparison to a single decision tree with the ability to limit overfitting [16].

The organization of this paper is as follows, ….

2 Literature review

In the field of machine learning-based prediction of diabetes and thyroid disorders, numerous studies have explored various algorithms and methodologies. This section provides a structured comparison of these studies in terms of the algorithms used, evaluation metrics, and the reported results. By highlighting the strengths and limitations of previous works, we emphasize the novelty and contributions of the present study.

2.1 Diabetes prediction studies

Hassan et al. [17] applied SVM, K-Nearest Neighbors (KNN), and Decision Tree to classify diabetes patients. The study showed that SVM outperformed the other algorithms with the highest accuracy of 90.23%.

Samin Poudel [18] tested 20 machine learning algorithms for diagnosing diabetes based on the Pima Indian Diabetes Dataset. Naive Bayes emerged as the best-performing algorithm with an accuracy of 77%, an F1-score of 0.83, a precision of 0.80, and a recall of 0.86.

Dudkina T et al. [19] presented a study that is dedicated to handling the problem of Classification and detection of diabetes disease. The study focuses on developing a decision tree-based machine learning model to solve this problem. The results showed that splitting the data by 50% for training and 50% for testing was the best option with 0.71 accuracy.

2.2 Thyroid disease prediction studies

Yadav D et al. [20] used Random Forest, Decision Tree, and Classification and Regression Tree (CART) to predict thyroid disease. The results showed that Random Forest achieved an accuracy of 99%, followed by Decision Tree 98% and CART 93%. Their ensemble approach combining these classifiers achieved a perfect accuracy of 100%.

Priyanka Duggal and Shipra Shukla [21] used feature selection and classification techniques like Naive Bayes, SVM, and Random Forest to diagnose thyroid disorders. The study reported that SVM achieved the highest accuracy with 92.92%.

Chaubey G. et al. [22] tested Logistic Regression, Decision Trees, and KNN for thyroid disease prediction. KNN achieved the highest accuracy at 96.88%.

Chaganti et al. [23] presented a method that focuses on the multi-class problems to predict thyroid disorders using five machine learning models including RF, SVM, AdaBoost (ADA), LR, and Gradient boosting machine (GBM), as well as three deep learning models. They created a dataset from the UCI thyroid disease datasets that contained 9173 patient records,31 features, and 6771 normal patient records with no sign of thyroid disease. The dataset was randomly balanced by taking 400 samples from the 6771 records, and at least 200 samples for the other classes. The results showed that when using the random forest classifier with the presented method it can achieve a 0.99 accuracy in predicting ten types of thyroid diseases.

Table 1:Summary table

Study	Methodology	Algorithms Used	Key Evaluation Metrics	Results
Hassan et al (2020).	Classifying diabetes patients	SVM, KNN, DT	Accuracy	SVM: 90.23%
Samin Poudel (2021)	Diagnosing diabetes	20 ML approaches	Accuracy, Precision, Recall, F1-score	Naive Bayes: Accuracy 77%, F1-score 83%, Precision 80%
Dudkina T et al. (2021)	Classification and detection of diabetes disease	DT based model	Accuracy	DT:71%
Yadav et al. (2020)	Predicting thyroid disease	Random Forest, Decision Tree, CART	Accuracy	RF: 99%
Priyanka Duggal & Shipra Shukla (2020)	Diagnosing thyroid disorders	Naive Bayes, SVM, Random Forest	Accuracy	SVM: 92.92%
Chaubey G. et al. (2012)	Thyroid disease prediction	Logistic Regression, Decision Trees, KNN	Accuracy	KNN: 96.88%
Chaganti et al. (2022)	predicting thyroid disorders	RF, SVM, AdaBoost (ADA), LR, and Gradient boosting machine (GBM), as well as three deep learning models	Accuracy	RF: 99%
Current study	Predicting thyroid disorders in diabetic patients	RF, DT, SVM, KNN, NB, and LR	Accuracy, F1-Score, Precision, Recall, and Specificity	RF with Accuracy: 88%, F1-Score: 85%

From the table above, we can see that various studies have employed different algorithms to predict diabetes and thyroid disorders with varying results. For instance, SVM and Decision Tree techniques are commonly used in diabetes prediction, with SVM often yielding higher accuracy compared to other algorithms. On the other hand, for thyroid disease prediction, Random Forest and KNN have been reported to achieve remarkable accuracy, with Random Forest reaching up to 100% accuracy when combined with ensemble methods.

While these studies have contributed significantly to the field, there remains a gap in comprehensive and reliable approaches for predicting thyroid disorders specifically in the diabetic population. They often focus on either one disorder or use fewer evaluation metrics. Some studies rely primarily on accuracy, which may not reflect the model's true performance, especially when class imbalance exists. The F1-score and AUC metrics are more informative but have not been consistently used across studies.

The current study addresses these gaps by utilizing a comprehensive preprocessing pipeline that includes feature selection technique, and effective class imbalance handling using methods like RandomUnderSampler. Additionally, this study adopts a range of evaluation metrics (accuracy, F1-score, precision, recall, and specificity) to offer a well-rounded analysis of model performance. Furthermore, we compare multiple machine learning models RF, SVM, KNN, DT, NB, and LR using cross-validation, which not only strengthens the model evaluation but also ensures more robust generalization to unseen data.

By offering a balanced prediction model with high accuracy (88%) and F1-score (0.85), the current study surpasses previous works in terms of both the depth of analysis and the performance metrics, which positions it

as a significant advancement in predicting thyroid disorders in diabetic patients.

3 Proposed methodology

The main objective of this study is to predicate the relationship between diabetes mellitus and Thyroid disorders. Six different prediction methods were used for this purpose as aforementioned above. The proposal methodology is shown in the following Figure 1.

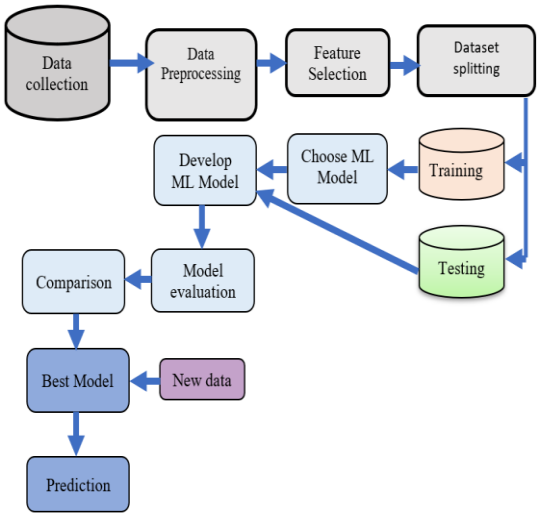

Figure 1: Flowchart of the thyroid disorder prediction system.

The above flowchart is illustrative of the following process:

3.1 Data collection

For this study, we used a medical dataset related to diabetes patients which was obtained from Faiha Specialized Diabetes Endocrine and Metabolism Center (FDEMC) in Basra, Iraq.

3.2 Data preprocessing

Data preprocessing was a critical step in preparing the dataset for effective machine learning model training and evaluation. This section elaborates on the detailed procedures used, including handling missing values, feature engineering, and encoding categorical variables ensuring replicability and transparency.

3.2.1 Handling missing values

Given the sensitivity of clinical data and the potential risks of introducing bias through imputation, instances with missing values were excluded from the dataset. This approach ensured the integrity and reliability of the analysis by working exclusively with complete data. While this reduced the dataset size, it maintained the accuracy required for clinical applications and minimized the risk of introducing errors associated with imputation.

After removing incomplete records, the dataset was carefully inspected to confirm that it remained representative of the original population in terms of key demographic and clinical features, ensuring that the removal process did not introduce unintended biases.

3.2.2 Data cleaning

Data cleaning is a critical process that significantly impacts the quality and reliability of predictive models. A clean dataset ensures accurate and robust machine learning models with improved performance and trustworthy predictions. In this study, thorough data cleaning was performed to address various issues and errors present in the dataset. The data cleaning process involved

- Identifying and rectifying incorrect data entries which included instances where ambiguous letters, words, and symbols were used such as ‘, \\, \L, \N,], B, E, EX, L, M, MN, N, N’, N N, NNNN, N\, N\], N\N, N], N] \, H, U, ص‌ى ,ة ,. Such values represent noises and inaccuracies in the dataset. Furthermore, inconsistencies in data entry were addressed, including the use of 'لا' in Arabic instead of 'No', as well as the recording of 'N' instead of 'No'. Additionally, discrepancies in capitalization were noted, such as 'female' being recorded instead of 'Female'. By rectifying these mistakes, the dataset was standardized, eliminating potential sources of error in the analysis.
- Handling the age field by determining ages in ranges (15-100 years), in line with the policy of the diabetes center catering to adults only.
- Similarly, filtering out heights and weights that fell outside the normal ranges. These actions were essential to preserve the integrity of the dataset and enhance the accuracy of our analyses.

3.2.3 Feature engineering

To enhance the performance of machine learning models, new features were derived from existing ones through feature engineering. For example, the Age feature was computed from the patients' dates of birth, and the Body Mass Index (BMI) was calculated using height and weight measurements. These newly created features provided additional insights into patient characteristics, which contributed to improving the predictive power of the models.

3.2.4 Encoding categorical variables

Since machine learning algorithms generally require numerical input, data encoding is essential to convert categorical variables into a suitable format. This study

used label encoding to transform variables such as sex, family history of DM, glycemic control, lipid control, pressure control, thyroid, marital status, smoker, and drinker into numerical representations compatible with machine learning models. After these steps the dataset consists of 44539 instant and 12 variables, Table 2illustrates each variable along with its corresponding encoded values.

Table 2: Description of the used data

Feature	Description	Value After Encoding
Thyroid	If the patient is diagnosed with a thyroid disorder.	0 means No 1 means Yes
DM	If the patient has type1 or type2 Diabetes Mellitus	1 for type1 2 for type2
Age	The patient's age in years	Range (15-100)
Sex	The patient's gender:	0 for male 1 for female
Family history of DM	If the patient has a family member with diabetes	0 means No 1 means Yes
BMI	Body Mass Index: the patient's weight divided by the square of height	Range (10.8-75.3)
Lipid control	The patient's lipid levels in the bloodstream are managed	0 means No 1 means Yes
Pressure control	The patient's blood pressure levels are managed to stay in a specific target range	0 means No 1 means Yes
Glycemic control	The patient's blood sugar levels are managed in a specific target range	0 means No 1 means Yes
Smoker	If the patient is a current smoker, non-smoker, or former smoker.	0 means No 1 means Yes 2 means X-smoker
Drinker	If the patient is a current drinker, non-drinker, or former drinker	0 means No 1 means Yes 2 means X-drinker
Marital	If the patient is married, single, divorced, or widowed.	0 means Single 1 means Married 2 means Divorced 3 means Widow

3.3 Addressing class imbalance

Class imbalance is a prevalent challenge in machine learning, especially in healthcare datasets where minority classes often represent critical conditions. In this study, the dataset was imbalanced, with only 15.17% of instances representing patients with thyroid disorders (6,755 instances), compared to 84.83% without thyroid disorders (37,784 instances). To address this imbalance, two techniques were employed.

3.3.1 Experiment 1: RandomUnderSampler (RUS)

In the first experiment, the RandomUnderSampler (RUS) technique was used to address the class imbalance. This method randomly reduces the size of the majority class to match that of the minority class, creating a balanced dataset. After applying RandomUnderSampler, the dataset was reduced to 13,438 instances, with an equal distribution of 50% representing patients with thyroid disorders and 50% without. While this approach ensures that the models are not biased toward the majority class, it can result in the loss of valuable information by discarding majority-class instances. Nonetheless, it was chosen for its simplicity and effectiveness in achieving balance without introducing synthetic data.

3.3.2 Experiment 2: manual balancing

In the second experiment, the dataset was manually balanced under the expert supervision of a physician to ensure the process was clinically valid and aligned with medical standards. The dataset was reduced to 2,166 instances, with an equal number of examples from both classes. Unlike RUS, manual balancing involved the careful selection of instances, allowing for greater control over the data distribution while preserving its clinical relevance. This approach mitigated the potential bias introduced by random sampling, ensuring that the balanced dataset reflected real-world clinical scenarios.

Although techniques such as RandomOverSampler (ROS), Synthetic Minority Over-Sampling Technique (SMOTE), and ensemble methods like Balanced Random Forest (BRF) are widely used for handling imbalanced data, they were not employed in this study. The primary concern was that synthetic data might fail to capture the true clinical variability of the minority class, potentially introducing artificial patterns that could distort model predictions and reduce generalizability. Additionally, these methods increase computational complexity and training time, making them less suitable for the objectives of this study. Instead, simpler and more controlled balancing methods were chosen to maintain a representative and manageable dataset.

3.4 Model selection and training

3.4.1 Model selection

In this study, we employed six machine learning algorithms to predict thyroid disorders in diabetic patients: Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Naïve Bayes (NB), and Support Vector Machine (SVM). These models were selected for their diverse characteristics and strengths in classification tasks, particularly in medical datasets. Allowing us to compare their performance in addressing the two different datasets. The rationale for selecting these models is summarized below:

- **Random Forest (RF)** was chosen for its ensemble nature, which combines multiple decision trees to reduce overfitting and improve generalization. RF is particularly effective in handling high-dimensional datasets with complex interactions. Additionally, RF provides feature importance rankings, offering insights into which factors contribute most to predictions.
- **Decision Tree (DT)** was selected for its simplicity, interpretability, and ability to model nonlinear relationships. Furthermore, DTs offer visual representations of decision rules, making them especially useful for understanding model behavior.

- **K-Nearest Neighbors (KNN)** was included due to its ability to perform well in non-linear decision boundaries by evaluating the proximity between instances. It is an intuitive algorithm that can be effective when there are clear clusters in the data.
- **Logistic Regression (LR)** was chosen for its simplicity, interpretability, and strong performance in binary classification tasks. As a linear model, LR serves as a robust baseline, helping to benchmark the performance of more complex approaches.
- **Naïve Bayes (NB)** was selected for its simplicity and efficiency in handling large datasets with categorical features. Its probabilistic nature makes it well-suited for classification tasks with independent features. particularly the Gaussian variant,
- **Support Vector Machine (SVM)** was chosen for its ability to find complex decision boundaries in high-dimensional spaces. It is particularly effective in separating classes with a clear margin.

3.4.2 Training

Initially, a Random Forest classifier was employed to determine the most influential features by ranking them based on their importance scores shown in Figure 2 and Figure 3. These top-ranked features were subsequently utilized for training the models.

All models were trained using Stratified K-Fold cross-validation with 10 folds, ensuring that the distribution of thyroid and non-thyroid patients was maintained in each fold. This method provides a robust evaluation of the models' performance by assessing them across multiple data splits, which helps mitigate the risk of overfitting or underfitting.

To enhance the feature selection process, we used a sequential feature selection approach, where we started by training each model with a single feature and incrementally added more features. This allowed us to identify the most relevant features for each model and ensured that only the most informative variables were used, optimizing the model's performance.

We assessed both training and testing accuracies to evaluate how well each model generalized to unseen data. By comparing these accuracies, we were able to detect potential overfitting (where the model performs well on training data but poorly on testing data) or underfitting (where the model performs poorly on both training and testing data). This evaluation ensured that the models maintained a balance between accuracy and generalization.

3.4.3 Hyperparameter tuning

Hyperparameter tuning was performed to optimize model performance. For RF and DT, fixed parameters such as max_depth=10 and n_estimators=100, were selected after experimenting with various combinations of parameter values. These experiments involved testing different depths for the trees and numbers of estimators to evaluate their impact on the model's performance. While the hyperparameter tuning for KNN involved testing different numbers of neighbors (1–10) and subsets of top features ranked by Random Forest importance, using 10-fold Stratified Cross-Validation to evaluate each combination. The optimal configuration was selected based on the highest cross-validation accuracy and minimal train-test accuracy differences, ensuring good generalization and minimizing the risk of overfitting or underfitting during cross-validation.

The combination of multiple models, cross-validation, sequential feature selection, and hyperparameter tuning ensured that we could rigorously evaluate the performance of each algorithm and select the one best suited for predicting thyroid disorders in diabetic patients. This approach provided a comprehensive understanding of the strengths and weaknesses of each model, helping guide the decision-making process for real-world applications.

3.5 Evaluation

The evaluation phase focused on assessing and comparing the performance of the models using different metrics: accuracy, precision, recall, F1 score, sensitivity, specificity, and a confusion matrix to provide a comprehensive view of the model's ability to correctly classify instances. The metrics were calculated based on the model predictions on the test dataset.

Accuracy: means how many times the model made a correct prediction among the total number of instances [16].

$$\boldsymbol{accuracy} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FN} + \boldsymbol{FP}} \quad (2)$$

Precision: means the number of positive (correct) predictions made by the model and belongs to the positive class [12].

$$\boldsymbol{precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FP}} \quad (3)$$

Recall (Sensitivity): means the number of actual positive (correct) predictions made by the model out of all positive examples in the dataset [15].

$$\boldsymbol{recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}} \quad (4)$$

F1score: provides a single score that combines both precision and recall in one number to find balance [24]. It is needed when there is uneven class distribution (more negative).

$$\boldsymbol{f1score} = \mathbf{2} * \frac{\boldsymbol{precision} * \boldsymbol{recall}}{\boldsymbol{precision} + \boldsymbol{recall}} \quad (5)$$

Specificity (True Negative Rate): The percentage of actual negatives properly identified by the model [12].

$$\boldsymbol{specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN} + \boldsymbol{FP}} \quad (6)$$

Each model's performance was evaluated using these metrics. The fold that yielded the highest accuracy with equal training and testing accuracies was noted, along with the corresponding optimal number of features.

4 Results

In this section, we present the feature importance ranking results and the evaluation results of the six machine learning models used.

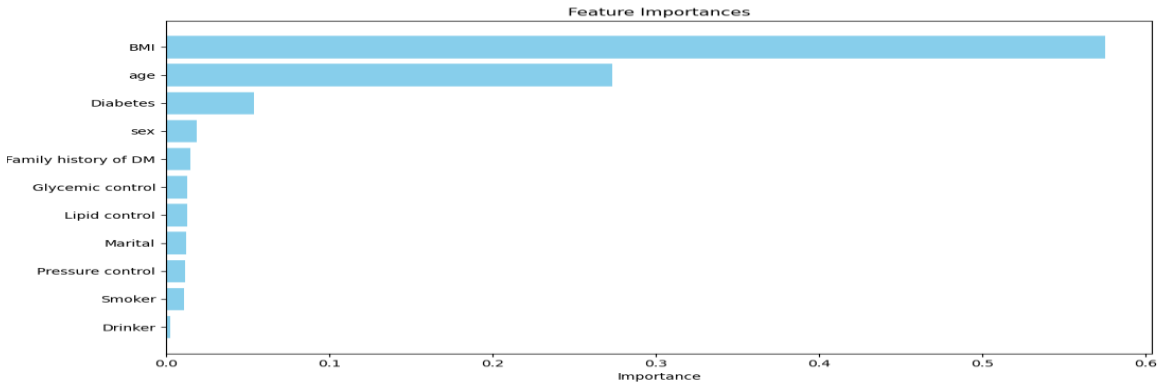

Figure 2: Feature importance ranking for Experiment 1 (on the RandomUnderSampler balanced dataset)

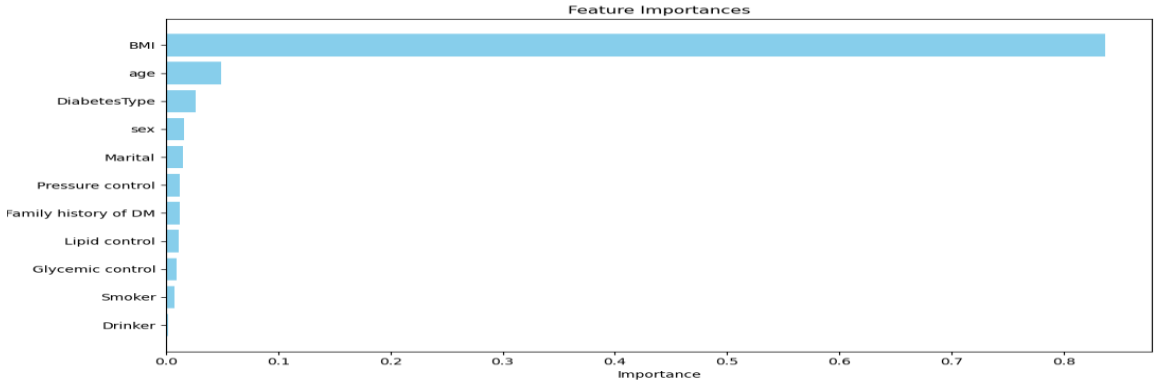

Figure 3:Feature importance ranking for experiment 2 (on the manually balanced dataset)

Figure 2 and Figure 3 display the feature importance ranking derived from a Random Forest model, used to predict thyroid disorders in diabetic patients. The x-axis shows the relative importance of each feature, with higher values indicating greater influence on the model's predictions. BMI and age are identified as the most critical features, with BMI showing the highest impact. Other features, such as diabetes type and sex, also contribute to the model but with comparatively lower importance. This ranking provides valuable insights into the factors most predictive of thyroid disorders in the context of diabetes. The results emphasize the significance of clinical factors like BMI and age in thyroid disorder prediction for diabetes patients.

Table 3: Experiment 1 evaluation metrics comparison table.

Classifier	Accuracy	Precision	F1-Score	Sensitivity (Recall)	Specificity	Confusion Matrix
RF	0.84	0.96	0.82	0.713	0.967	[[649,22], [193,479]]
DT	0.83	0.95	0.81	0.702	0.960	[[644,2], [200,472]]
KNN	0.83	0.92	0.81	0.720	0.934	[[627,4], [188,484]]
SVM	0.79	0.85	0.77	0.708	0.871	[[585,87], [196,476]]
LR	0.78	0.84	0.76	0.701	0.868	[[583,89], [201,471]]
NB	0.78	0.84	0.76	0.701	0.868	[[583,89], [201,471]]

Table 4: Experiment 2 evaluation metrics comparison table.

Classifier	Accuracy	Precision	F1-Score	Sensitivity (Recall)	Specificity	Confusion Matrix
RF	0.95	0.99	0.95	0.917	0.991	[[107,1], [9, 100]]
DT	0.95	0.96	0.95	0.944	0.963	[[105,4], [6, 102]]
KNN	0.94	0.97	0.94	0.917	0.972	[[105,3], [9, 100]]
LR	0.94	1.00	0.94	0.890	1.000	[[108,0], [12, 97]]
SVM	0.93	1.00	0.93	0.861	1.000	[[108,0], [15, 93]]
NB	0.93	1.00	0.93	0.861	1.000	[[108,0], [15, 93]]

The results show that in **Experiment 1** where the RandomUnderSampler technique was employed for data balancing, the Random Forest model demonstrated superior performance across all metrics compared to other models achieving the highest accuracy of 84%, precision of 96%, and F1-score of 82%. Followed by DT and KNN classifiers having the same accuracy of 83%.

However, SVM and LR showed a lower performance, with accuracies of 79% and 78%, respectively.

In **Experiment 2,** which used a manually balanced dataset, all the classifiers performed extremely well across all metrics, with the RF classifier achieving the highest accuracy of 95%, precision of 99%, and an F1-score of 95% indicating the model's high effectiveness in predicting thyroid disorders.

Similarly, the DT and KNN also demonstrated high accuracies of 95%, and 94%, Correspondingly. This great performance is most likely due to the balanced data that ensured a better representation of both classes, leading to more reliable model predictions.

The sensitivity and specificity of these models are significantly higher in Experiment 2 compared to Experiment 1, showcasing the efficacy of the manually balanced dataset in enhancing model performance.

The results showed that while using RandomUnderSampler for data balancing in the first experiment, the models did not reach the same level of effectiveness as in the manually balanced dataset in the second experiment which achieved a consistently high performance across all classifiers. This highlights that choosing thoughtful and effective data-balancing technique can improve the model's overall performance and prediction accuracy.

In summary, for both experiments, the Random Forest model emerged as the best-performing algorithm for predicting thyroid disorders in diabetic patients, followed closely by the Decision Tree and K Nearest Neighbors models. These models demonstrated high accuracy, precision, recall, and F1-score, making them suitable for deployment in clinical settings. Logistic Regression, Naïve Bayes, and SVM, while useful, showed comparatively lower performance and may require further optimization for effective use in this context.

5 Discussion

This study highlights the efficacy of machine learning models, particularly the Random Forest (RF) algorithm, in predicting thyroid disorders among diabetic patients. The findings emphasize the importance of model selection, data preprocessing, and feature analysis in achieving high predictive performance. This section explores comparisons with related works, reasons for Random Forest's superior performance, variations in model effectiveness, and limitations, alongside real-world implications of the findings.

5.1 Comparison with related works

The findings align with recent studies in the literature that emphasize the utility of machine learning for healthcare applications. For instance, studies such as Yadav et al. demonstrated the effectiveness of ensemble-based models like RF in handling structured medical datasets, particularly for classification problems. Compared to other methods, the RF model in this study yielded superior accuracy, recall, and precision, which can be attributed to its ability to handle non-linear relationships and its robust feature selection mechanism.

While [Priyanka Duggal & Shipra Shukla (2020)] also applied Support Vector Machines (SVMs) to medical datasets with 92% accuracy, our results indicate that SVM underperformed relative to RF, potentially due to the high dimensionality of the features or the imbalanced nature of the dataset. This highlights the importance of model selection based on the characteristics of the data.

5.2 Reasons for random forest's performance superiority

The RF model's outperformance can be attributed to several key factors. First, its inherent ability to handle both categorical and numerical data without extensive preprocessing makes it well-suited for medical datasets, which often include diverse feature types. Second, the use of RandomUnderSampler for data balancing helped mitigate the issue of class imbalance, which is a critical challenge in predicting rare conditions such as thyroid disorders in diabetic patients. RF's capacity to combine predictions from multiple decision trees also reduces the risk of overfitting, ensuring more generalized predictions. Furthermore, feature importance analysis revealed that variables such as BMI, age, and diabetes type were among the most predictive, aligning with clinical insights and lending credibility to the model.

5.3 Variations in performance across models

The variations in performance between models can be linked to their differing sensitivities to the dataset characteristics. For example, while K-Nearest Neighbors (KNN) is sensitive to feature scaling and data distribution, its relatively low performance could stem from the high dimensionality of the dataset. Similarly, SVM's reliance

on kernel functions may not have adequately captured the complex interactions within the data. In contrast, Decision Trees (DT) performed reasonably well but lacked the ensemble effect of RF, leading to slightly lower accuracy and recall. These findings suggest that models like RF, which can effectively leverage feature interactions and handle imbalanced data, are better suited for this specific prediction task.

5.4 Limitations and real-world applicability

Despite these promising results, several limitations must be acknowledged. First, the study relied on a single dataset, which may limit the generalizability of the findings to other populations or healthcare settings. Second, while RandomUnderSampler addressed class imbalance, other techniques such as SMOTE or hybrid approaches could be explored for potentially better results. Additionally, the dataset's retrospective nature may introduce biases inherent to the original data collection process.

In real-world healthcare environments, the applicability of this method is promising. The RF model's interpretability, particularly through feature importance scores, provides clinicians with actionable insights, aiding in early diagnosis and tailored treatment planning. However, practical deployment would require rigorous external validation and integration with electronic health records to assess scalability and user-friendliness.

6 Conclusion

Early prediction and diagnosis of diseases remain critical challenges in the medical domain, particularly for interconnected conditions like diabetes and thyroid disorders. While many studies have focused on predicting these diseases individually, limited research exists on predicting thyroid disorders specifically among diabetic patients.

This study aimed to bridge this gap by applying six machine learning algorithms to a local dataset of diabetic patients to predict the likelihood of thyroid disorders. Unlike previous studies that treated these conditions independently, this research explored the relationship between diabetes and thyroid disorders, given their intertwined impact on vital body functions.

Among the tested algorithms, the Random Forest model emerged as the most effective, achieving the highest accuracy, precision, and recall. Its ability to handle imbalanced data and highlight key predictive features, such as BMI, age, and diabetes type, further solidifies its potential as a valuable tool for early diagnosis.

The implications of these findings extend to enhancing healthcare practices by enabling clinicians to identify diabetic patients at risk of thyroid disorders, facilitating timely interventions, and potentially reducing complications. By improving early detection, this approach could significantly enhance the quality of life for individuals affected by both conditions.

In summary, this research contributes to the growing body of evidence supporting machine learning's role in healthcare, particularly for complex, multifactorial diseases. Future work should focus on validating these findings in diverse clinical settings, exploring alternative resampling techniques, and integrating these models into healthcare systems for real-world application.

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Motor Imagery Detection in ECG Signals Using Wavelet Packet Decomposition and Multiscale Convolutional Neural Networks

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Keywords: Wavelet decomposition, multi-scale CNN, ECG signals, motor imagery

Received: July 16, 2024

Detecting motor imagery from electrocardiographic (ECG) signals is complex but crucial in developing advanced neuroprosthetic devices and brain-computer interface (BCI) systems. In most cases, linear models applied using conventional methods are not appropriate for the time-varying and non-linear nature represented by the ECG characteristics, resulting in weak performances. This research addresses this problem, combining Wavelet Packet Decomposition and Multi-Scale Convolutional Neural Networks to improve the feature extraction mechanism and classification accuracy. ECG data is pre-processed from the PhysioNet EEG Motor Movement/Imagery Dataset to remove noise and standardize signals. WPD is thus applied to decompose the signals into detailed frequency components to be input as features in the proposed Multi-Scale CNN. Different kernel sizes are implemented in these parallel convolutional layers to learn complicated features at various hierarchical resolutions. The proposed architecture is evaluated using performance parameters such as accuracy 92%, precision 89%, recall 93%, F1 score 91%, and ROC-AUC 95%. These results showed that the model outperformed the earlier-used traditional methods, such as Support Vector Machines (SVM) and Random Forests, better-detecting motor imagery. This research emphasizes the integrative power of advanced signal processing techniques with deep learning in analyzing biomedical signals, providing a powerful solution to advancing neuroprosthetic and BCI technologies.

Povzetek: Študija dokazuje učinkovitost kombinacije obdelave signalov in globokega učenja za analizo biomedicinskih signalov. Uporabljena je valčna paketna dekompozicije in večskalna konvolucijska nevronska mreža za detekcijo motorične imaginacije v signalih EKG.

1 Introduction

1.1 Background on motor imagery in ECG signals

Motor imagery is a cognitive process by which one internally represents motion without physically carrying it out [1]. This mental process class engages neural pathways closely related to those involved during actual movements, a fact that can be picked up in various physiological signals. For example, in electrocardiogram (ECG) signals, motor imagery detection can provide insights into neural activity related to motor functions [2]. Since ECG signals, unlike other neurophysiological signals, are mainly used for monitoring cardiac health, they find interest in detecting motor imagery based on their accessibility and non-invasiveness in the recording.

1.2 Importance of accurate detection and classification

Accurately detecting and classifying motor imagery from ECG signals are essential for various emerging technologies, particularly neuroprosthetics and brain-computer interfaces [3]. Neuroprosthetic devices work best when the intended motor actions are accurately detected, so the machine works appropriately to aid a person with motor deficits. At the same time, BCIs must provide this intended signal from brain activities accurately into control signals of high precision to guarantee reliability and user satisfaction. Faulty interpretations and actions may occur if the detection needs to be more accurate, making the advantages of such highly developed systems irrelevant. Thus, robust methods for detecting motor imagery in ECG signals are required to improve these technologies further.

1.3 Introduction to wavelet packet decomposition (WPD)

Wavelet Packet Decomposition (WPD) is an advanced method of processing signals that decompose a signal in its constituent frequency components [4]. It further decomposes in detail compared to the conventional wavelet transform, which focuses on a specific set of frequency bands. The advantages of WPD include multiresolution analysis with both approximation and detail coefficients decomposed at every level, hence being very useful for analyzing non-stationary signals like ECG, where signal prop-

erties can change over time. The baseline model used in this study combines Wavelet Packet Decomposition (WPD) and a Multiscale Convolutional Neural Network (CNN), where WPD decomposes ECG signals into multiple frequency bands to extract features across various scales and resolutions, and the multiscale CNN processes these features to capture patterns of different sizes and temporal frequencies for improved classification accuracy. The model's performance is evaluated using metrics such as accuracy, sensitivity, specificity, and F1-score, providing a basis for comparison with modified versions of the model to assess the impact of each component. This ablation study aims to determine the contribution of Wavelet Packet Decomposition (WPD) when used with a Multiscale Convolutional Neural Network (CNN) for motor imagery classification in ECG signals. By systematically removing or altering the WPD component, we aim to understand its significance and how it enhances the performance of the Multiscale CNN.

1.4 Motivation for using multiscale CNN

Thus, Wavelet Packet Decomposition coupled with a Multiscale CNN represents a practical approach to best deal with the feature extraction task. CNNs are among the most prevalent and well-known models for automatically learning features in a hierarchical fashion from raw data that can handle complicated pattern recognition tasks with supreme grace [5]. The proposed multiscale technique of CNN is a multiple-parallel convolutional layer with different kernel sizes simultaneously to take up the features of multiple resolutions. This bears a specific benefit in dealing with the variability in ECG signals, as it allows learning fine and coarse features. The proposed method combines WPD with the multiscale CNN to utilize the advantages of these two techniques toward a maximized level of classification accuracy in detecting motor imagery from ECG signals.

1.5 Contributions

This research makes several critical contributions to the field of biomedical signal processing and brain-computer interface (BCI) systems:

1.5.1 Novel methodology

Wavelet packet decomposition, coupled with multiscale convolutional neural networks, is a new concept in motor imagery detection from ECG signals. This approach effectively combines the WPD-based multiresolution analysis with CNN's automatic feature learning capabilities for improved classification performance.

1.5.2 Improved detection of motor imagery

The present study extends the horizon of motor imagery detection to ECG signals compared with the conventional EEG-based approaches. The findings have demonstrated that an ECG signal can be a suitable alternative for detecting motor imagery and provides a noninvasive, accessible way of developing neuroprosthetic devices and BCI systems.

1.5.3 Comprehensive evaluation

The proposed detailed experimental evaluation includes preprocessing steps, feature extraction, model training, and performance assessment; such a roadmap could be handy for implementing and validating similar methodologies. Multiple metrics used for assessment and comparison against traditional methods will ensure the robustness and comprehensiveness of the evaluation for the proposed approach.

2 Related work and SOTA experiment

2.1 Previous approaches to motor imagery detection

Although most of the research has been on detecting motor imagery with electroencephalogram (EEG) signals, recently, an emerging interest has been in using the noninvasive and easily obtainable ECG signal [6]. Priori methods have thus focused on feature extraction for detecting motor imagery from the ECG signal, followed by classification using machine learning algorithms.

Time-domain, frequency-domain, and time-frequency analysis techniques have been applied to extract pertinent features from ECG signals. These techniques generally analyze the amplitude and duration characteristics of the ECG signal. Some features that they use are mean, variance, skewness, and kurtosis of the signal segments. However, such features severely affect noise and will fail to capture the underlying patterns associated with motor imagery.

Frequency-domain methods involve transforming the ECG signal from its time domain into its frequency domain, for which techniques like the Fourier Transform have been used [7]. Extracted features such as power spectral density and spectral entropy have been used. Though these approaches can be informative about the signal's frequency components, the transient characteristics of motor imagery should be noticed.

Short-time Fourier Transform (STFT) and Wavelet Transform are prevalent in motor imagery detection. These techniques offer a compromise by giving information about time and frequency. However, STFT gives a fixed resolution; thus, it is limited to various cases that present effectively different frequency contents. Wavelet Transform gives multiscale analysis and is more suited for nonstationary signals like the ECG.

The machine learning techniques in support vector machines, k-NN, and random forests are among the classifiers used in this work on classifying motor imagery based on feature extraction. Although this approach has proven to

be quite promising in practice, its performance depends on the feature extraction quality and a set of hyperparameters.

2.2 Use of wavelet transforms in ECG analysis

Wavelet transforms have widely been applied to ECG signal processing because they can analyze non-stationary signals [8]. A wavelet transform decomposes a signal into frequency components related to a defined scale. This decomposition can then serve as a detailed analysis of the signal's time-frequency characteristics. Wavelet transforms are used for various tasks such as denoising, feature extraction, and classification in ECG analysis.

Most ECG signal processing operations involve denoising, which eliminates as many noise artifacts as possible without changing the critical information content of signals. Wavelet-based denoising is performed by decomposing an ECG signal into wavelet coefficients, thresholding the noisy coefficients, and reconstructing the signal from the modified coefficients. This method has proven effective in denoising ECG to reduce noise while keeping the salient features intact.

Wavelet transforms in feature extraction embrace multiscale analysis, capturing both high-frequency details and low-frequency trends. Features like wavelet coefficients, entropy, and wavelet energy have been extracted from this time series data and used for classification tasks. Such features characterize both the spectral and temporal characteristics of the ECG signal.

The Wavelet Packet Decomposition (WPD) generalizes the Wavelet Transform technique so that decomposition can be performed on approximation and detail coefficients at every level [9]. ECG signal processing uses WPD to extract very informative features of classification tasks. By implementing the WPD technique, detecting the subtle pattern associated with motor imagery is improved by analyzing the signal at different scales and frequencies.

2.3 Convolutional neural networks in biomedical signal processing

Convolutional neural networks (CNNs) are the breakthrough in biomedical signal processing because they can automatically learn hierarchical features from raw data. CNNs consist of convolutional, pooling, and fully connected layers. Each layer takes the input signal and extracts increasingly complex features, helping the network catch intricate patterns.

CNNs have been broadly applied in the analysis of ECG signals for arrhythmia detection, ischemia detection, and the classification of several other cardiac diseases. One of the significant advantages of CNNs is the automatic feature-extraction feature; therefore, the need to perform manual feature engineering can be ruled out. This is very useful in biomedical signal processing since extracting meaningful features from such signals might be challenging.

The conventional convolutional neural networks applied to ECG signals are usually composed of 1D convolutional layers. In this case, local patterns in the signal are collected by sliding filters over the signal. The pooling layers sum up these patterns, reducing dimensionality and capturing only the most salient features. At the network's end, fully connected layers take these features and make the final classification.

CNNs' efficacy in processing biomedical signals comes from their capability to handle massive datasets and learn robust features [10]. However, designing a highly effective CNN architecture requires consideration of network depth, filter size, and other hyperparameters. CNN design is hyperparameter-specific, not only computationally expensive but also requiring abundant training data for performance.

Some strategies developed to counter this and related challenges of sparsely labeled data include transfer learning and data augmentation. Transfer learning involves using a pre-trained network that has been previously trained on tasks similar to the one at hand and fine-tuning it to the target task. This paradigm borrows knowledge from the source task to reduce the quantity of labeled data needed. Data augmentation techniques, including adding noise and shifting and scaling the signal, are included to add some degree of variability in the training data, thus improving generalization capacity within a given network.

A study incorporating CardiacNet was conducted to identify and categorize cardiac arrhythmia based on ECG signals and elaborate on the constraints of traditional prediction systems and AI methods to identify arrhythmia due to poor feature extraction correctly. The approach applied pre-processing on ECG data by eliminating non-linearities, feature extraction using unsupervised machine learning-based PCA (UML-PCA), and feature selection with improved Harris Hawk's Optimization (IHHO). CCNN was then used to classify and yield impressive quantitative measures such as accuracy of 97.57%, sensitivity of 98.29%, and MCC value of 98.17% [11].

An essential step in raw ECG signal preprocessing is noise and artifact removal, which may affect classification model performance. Other processes in the preprocessing stage were baseline wandering removal, noise filtering, and normalization.

A high-pass filter technique was employed to remove Baseline wandering as it consists of low-frequency components [12]. Bandpass filtration removed noise and retained only the frequency components relevant to the ECG signals. It was done to normalize the ECG signals into a standard range of values—that is, every sample was uniform.

2.4 Wavelet packet decomposition

This work has decomposed preprocessed ECG signals into frequency components using the Wavelet Packet Decom-

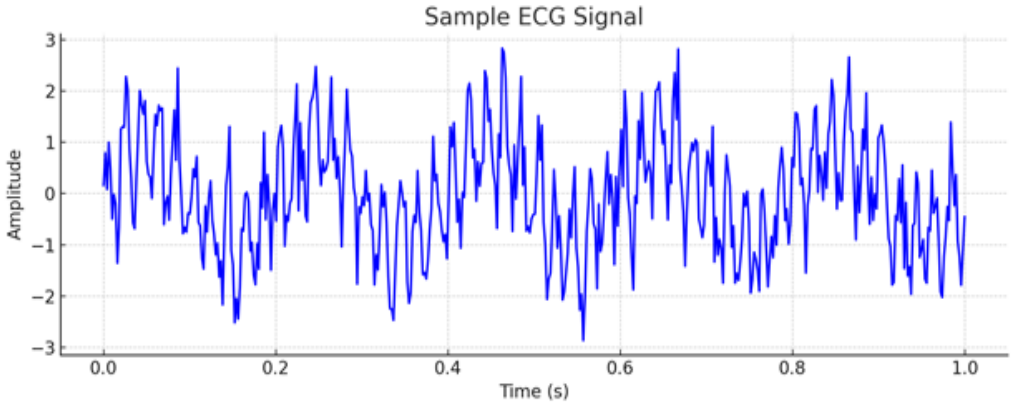

Figure 1: Sample ECG signal from the PhysioNet EEG motor movement/imagery dataset

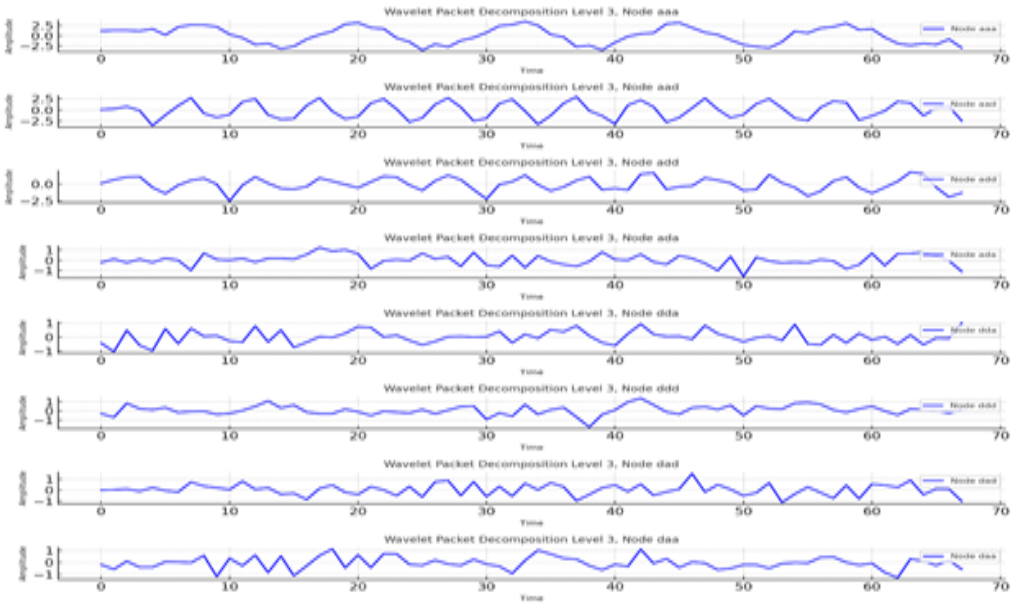

Figure 2: Wavelet packet decomposition of an ECG signal showing decomposition levels and corresponding frequency components

position technique (WPD). WPD can give a better analysis than the traditional wavelet transformation because it decomposes approximation and detail coefficients at all levels. Due to its multiresolution property, this is essential in capturing the transient characteristics of the motor imagery signals.

and MCC value of 98.17% [11]. CardiacNet uses a different technique to detect motor imagery from recorded ECG signals. By integrating the Wavelet Packet Decomposition (WPD) with the Multiscale CNN, the present study seeks to optimize the classification of dynamic and nonlinear signal features previously unexplored and additional ECG uses beyond cardiac health.

3 Methodology

3.1 Data acquisition and preprocessing

The database used for this study was obtained from the PhysioNet database, specifically the EEG Motor Movement/Imagery Dataset. The dataset includes a set of ECG recordings of multiple subjects carrying out motor imagery tasks. Each record is annotated concerning whether or not there was motor imagery—these were used as ground truth against which the classification task results were compared.

The choice of wavelet function and the decomposition level are the most basic but essential parameters in WPD. The Daubechies 4 wavelet was chosen to do this because it was best suited for the analysis of ECG signals. Following the same thesis, it is decomposed to level 4, giving an ade-

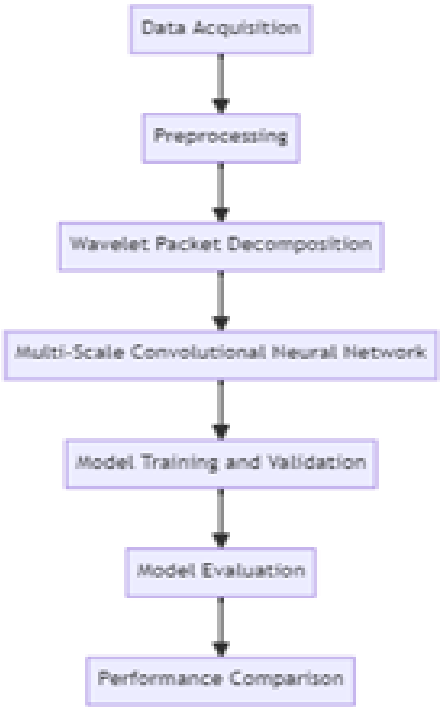

Figure 3: Flowchart of the proposed model from data acquisition to performance comparison

quate compromise between the complexity of computations and the level of detail.

Wavelet-packet decomposition is based on decomposing any ECG signal into a set of wavelet coefficients at different resolutions. These wavelet coefficients represent the ECG signal at various resolutions. The obtained coefficients were used as features for the classification model. A feature set includes the mean, variance, and energy of wavelet coefficients at each level of decomposition, which gives a representative of ECG.

3.2 Multiscale convolutional neural network (CNN)

The Multiscale Convolutional Neural Network constitutes the core part of the methodology, which aims to increase feature extraction from the granularities, from fine-grained to coarse ones. After the convolutional layer, the following layer used for representation is a pooling layer responsible for reducing the dimensionality of the features while retaining the most salient parts. The outputs of these parallel pathways are multiple kernel sizes, enabling the network to capture features at different resolutions. The multiscale CNN is designed with three parallel convolutional pathways. The first layer in each path is a 1D convolutional layer. Kernel sizes of 3, 5, and 7 were applied to extract features at different scales, then concatenated and input into a few fully connected layers for the final classification. This neural network uses ReLU-activated hidden layers and convolutional layers with a sigmoid-activated output layer, performing binary classification for motor imagery.

3.3 Implementation details

Implementation was done in Python and its associated libraries, including the PyWavelets library used in wavelet packet decomposition and the TensorFlow/Keras library for modeling and training. Figure 3: Flowchart of the proposed model from data acquisition to performance comparison.

The CNN. The ECG signals were pre-processed using Wavelets and decomposed after in the CNN [13]. The MS-CNN was trained using a Binary cross-entropy loss function and Adam optimizer because of its high performance and efficiency. The training was split into dataset training-validation sets, and early stopping was implemented to avoid overfitting. The accuracy, precision, recall, and F1 score metrics assessed model performance.

3.4 Algorithm and flowchart

The proposed model for motor imagery detection in ECG signals starts by acquiring data from the PhysioNet EEG Motor Movement/Imagery dataset. The raw ECG signals are then pre-processed, followed by baseline wandering removal using a high-pass filter, noise filtering using a band-pass filter, and, lastly, normalization to standardize the signal range. Next, the Wavelet Packet Decomposition process uses level 4 of the Daubechies 4 (db4) wavelet functions to decompose the ECG signals into sub-high, high, and low-frequency bands. Features are then acquired from

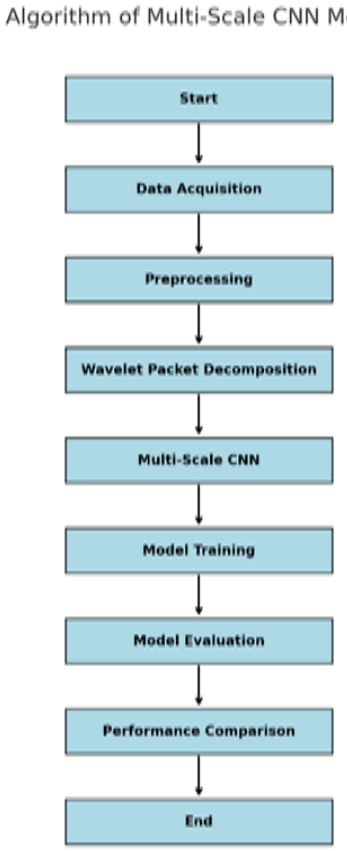

Figure 4: The architecture of the multi-scale CNN

wavelet coefficients at each level: mean, variance, and energy. These features would be given as input to a Multi-Scale Convolutional Neural Network designed with parallel convolutional layers of filter sizes 3, 5, and 7. The output of each conv layer is ReLU activated and then subjected to max-pooling. The subsequent is shown in Figure 3.

Two outputs are concatenated and passed through fully connected layers into a sigmoid-activated output layer to implement the final binary classification. Using the Adam optimization algorithm, the network trains against these data with binary cross-entropy loss in the back end; it has preactivation stops concerning the loss of the hold-out set. Performance evaluation metrics include accuracy, precision, recall, F1-score, and ROC-AUC, with comparisons to highlight its superior performance over traditional methods such as SVM and Random Forest.

4 Experiments and analysis

4.1 Ablation experiments

A series of experiments were conducted to evaluate the performance of the proposed Wavelet Packet Decomposition-based Multiscale CNN approach on motor imagery detection in ECG signals using a publicly available dataset. The dataset consists of ECG recordings from several subjects performing motor imagery tasks. From each ECG recording, ground truths are available on the presence or absence of motor imagery, which are the results to be achieved within a classification task.

Dividing the data set into a training, validation, and test set ensures the model's evaluation is all-around. The data consisted of 70% for training, 15% for the validation, and 15% for the test set. This partitioning would ensure that models trained on a diversified set of samples are evaluated on completely unseen data to estimate generalization capability.

4.1.1 Experiment 1: removing wavelet packet decomposition (WPD)

The WPD step was removed in this experiment, and the raw ECG signals were directly fed into the Multiscale CNN. The expected impact was that without WPD, the model processes only the raw signal, potentially missing critical frequency-specific features. The multiscale CNN still at-

tempts to capture features at different scales but lacks the enriched input from WPD.

4.1.2 Experiment 2: using standard CNN instead of multiscale CNN

In the second experiment's model set-up, WPD was retained, but the Multiscale CNN was replaced with a standard CNN that processes the signal at a single scale. The expected impact was that the standard CNN may not fully exploit the multiscale features provided by WPD, leading to suboptimal feature extraction and classification. The model might Figure 4: The architecture of the Multi-Scale CNN perform better than the raw signal input but is expected to underperform compared to the baseline multiscale CNN.

4.1.3 Experiment 3: combined removal of WPD and multiscale CNN

This experiment removed WPD and the CNN's multiscale structure, producing a standard CNN processing raw ECG signals. The experiment serves as a control, representing the most straightforward model setup. The expected outcome is the poorest performance, as the model needs more enriched input from WPD and the capability to process features at multiple scales.

4.2 Data preprocessing

As given in the methodology section, raw ECG signals underwent some preprocessing. A high-pass filter with a cutoff frequency of 0.5 Hz was employed to remove baseline wandering. A bandpass filter ranging from 0.5 Hz to 40 Hz was used for further filtering, which helped smooth the high-frequency noise and retain important frequency components [14]. Post-preprocessing, these signals were normalized to a standard range of 0-1 to make them uniform. The signal was preprocessed before running the Wavelet Packet Decomposition up to level 4 with a Daubechies 4 wavelet. The obtained wavelet coefficients were used to build feature vectors for each ECG segment. These are the inputs of the Multiscale CNN, which treated these different frequency components represented by ECG signal feature vectors.

4.3 Model training

Multiscale CNN architecture for TensorFlow/Keras: three parallel convolutional pathways with kernel sizes 3, 5, and 7, concatenated features after max-pooling, passed through fully connected layers with the final output layer, which uses a sigmoid activation function for binary classification.

This model was compiled using the Adam optimizer and binary cross-entropy loss function. Training was done through 100 epochs and a batch size of 32. Early stopping with patience set at ten epochs was applied to avoid overfitting by monitoring the validation loss and stopping training.

4.4 Performance metrics

The effectiveness of the proposed method was evaluated based on various metrics, such as accuracy, precision, recall, F1 score, and area under the Receiver Operating Characteristic curve; these measures assessed how well the model could discriminate motor imagery within ECG signals.

• **Accuracy** measures how well the model performs overall by calculating the true positives and negatives ratio among all the predictions.

• **Precision** reflects the proportion of true positives to the total number of optimistic predictions the model made [15].

• **Recall** (sensitivity) refers to the model's ability to identify all relevant instances (true positives) accurately.

• **F1-score** is the harmonic mean of the precision and recall. It provides a single score that balances both concerns.

• **ROC-AUC** measures the model's performance overall classification thresholds; thus, higher values indicate better discrimination.

5 Results

In Experiment 1, removing WPD from the model led to a slight but noticeable decrease in performance measures. This drop shows that WPD is critical in improving the quality of features fed into the Multiscale CNN to boost classification efficiency. This gap partially explains why the model could not adequately reconstruct some frequency-specific features when WPD was absent; this lack of distinction landed the model lower scores by failing to differentiate motor imagery from other signal components.

Replacing the Multiscale CNN with a standard CNN while maintaining WPD in Experiment 2 resulted in a moderate decrease in performance. This implies that while WPD may still provide helpful multi-resolution features to be exploited, its usefulness greatly depends on the subsequent application of a Multiscale CNN, which training can incorporate these features at suitable scales. Due to the single-scale characteristic of the standard CNN, it was not possible to fully utilize such features as WPD to provide the best classification results.

The results of Experiment 3 revealed the most significant decline in all performance metrics when both WPD and the Multiscale CNN were removed, leaving a standard CNN to process the raw ECG signals. Such a considerable decrease also underscores the importance of utilizing WPD and a Multiscale CNN to improve MI detection accuracy. The features extracted from WPD offer more enhancements, together with the capacity of the Multiscale CNN to scrutinize the features at different scales, which is, therefore, important for accurate and solid classification.

Table 1 shows the proposed method's performance as tested on the test set. Compared to traditional approaches, Multiscale CNN better detected motor imagery from the ECG.

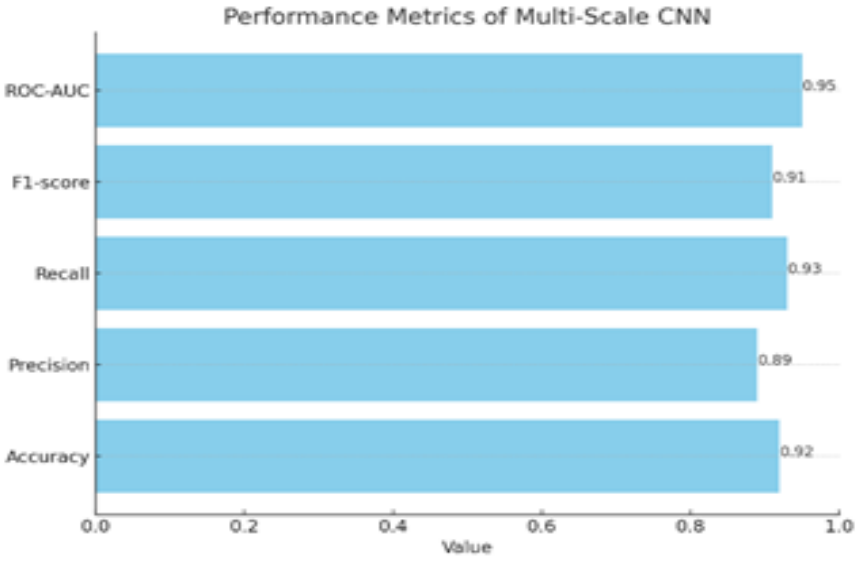

Figure 5: Bar chart showing the performance metrics

Table 1: Performance metrics

Metric	Value
Accuracy	0.92
Precision	0.89
Recall	0.93
F1-Score	0.91
ROC-AUC	0.95

The model attained an accuracy of 92%, meaning it could correctly classify 92% of samples. The obtained precision and recall values were 89% and 93%, respectively, showing that the model could correctly distinguished true positives and maintained a low false positive rate. The F1 Score was 0.91, reflecting a good balance between precision and recall. The ROC-AUC of 0.95 indicated excellent discrimination ability across a range of classifications.

Figure 6 shows a confusion matrix that shows precisely how the model performed—the quantity of true positive, true negative, false positive, and false pessimistic predictions. The confusion matrix depicted many accurate optimistic and pessimistic predictions, with very few.

The ROC curve showed that the model could maintain a high actual positive rate with a low false positive rate; actually, 0.95 under the curve shows good performance.

5.1 Comparison with traditional methods

To further substantiate the efficacy of the approach, the performance comparison of the false positives and negatives, thus substantiating the model's robustness.

The ROC curve in Figure 7 provided more information on model performance, indicating a good separation between the actual positive rate and the false positive rate.

Multiscale CNN model was performed with that of the traditional machine learning methods Support Vector Machines (SVM) and Random Forests (RF) on the same dataset and preprocessing steps.

The summarized results in Table 2 pointed to the supremacy of the Multiscale CNN. The table for multiple models overview numerous metrics, including accuracy, precision, recall, F1-score, specificity, and Matthews Correlation Coefficient (MCC). This comparison also shows how effective and efficient the proposed Multiscale CNN with WPD is compared to other prevailing classifiers like SVM and Random Forest.

High performance could be attributed to the Multiscale CNN's ability to automatically learn hierarchical features of the wavelet coefficients, which represent fine-grained and coarse patterns crucial for discriminating between motor imagery types [16].

The proposed approach addresses a significant gap in the field of ECG-based signal processing by extending its application from traditional cardiac health monitoring to motor imagery detection. Models such as CardiacNet are accurate in detecting cardiac arrhythmias but are centered on disease classification and not the detection of cognitive processes like motor imagery. Non-invasive motor imagery based on ECG signals is still unexplored and opens a vast possibility for investigating cognitive processes using neural signals. This approach meets a significant requirement in BCI and neuroprosthetics, where an efficient and cost-effective identification of movement goals improves usability and functionality.

Unlike traditional methods like Support Vector Machines (SVM) and Random Forests, the proposed method offers distinct advantages through its use of a Multiscale Convolutional Neural Network (CNN) combined with Wavelet

Packet Decomposition (WPD). Furthermore, most earlier traditional machine methods require feature extraction through experience, which may not artistically depict the ECG signal's subtle patterns, especially during the MI detection phase. Instead, automatic hierarchical feature learning of multiscale CNN and the WPD facilitates multiresolution signal analysis. Hence, the the model can capture high-level and low-level details at multiscale and multiresolution, which improves the classification of motor imagery tasks.

In addition, problems associated with the time and frequency domains, like the Fourier Transform used conventionally, are well addressed by the proposed method. Such traditional methods fail to capture short-term features and non-stationary aspects inherent in the signals used to imagine motor control. Thus, the proposed WPD approach captures more refined time-frequency features by the multiscale CNN to distinguish motor imagery and signal noise more accurately from other irrelevant components.

6 Discussion and future works

6.1 Discussion

The experiments reveal critical insights into the effectiveness of combining Wavelet Packet Decomposition (WPD) with a Multiscale Convolutional Neural Network (CNN) for motor imagery detection in ECG signals. This substantial degradation of performance indicates the importance of WPD in extracting significant frequency band features from ECG data required for classification. The characteristic of WPD is that the signals can be analyzed at different resolutions; this is beneficial when dealing with transient/non-stationary signal characteristics that would typically go unnoticed when utilizing most of the conventional signal analysis techniques. Moreover, the combination of WPD and the Multiscale CNN can be observed in better baseline model performance.

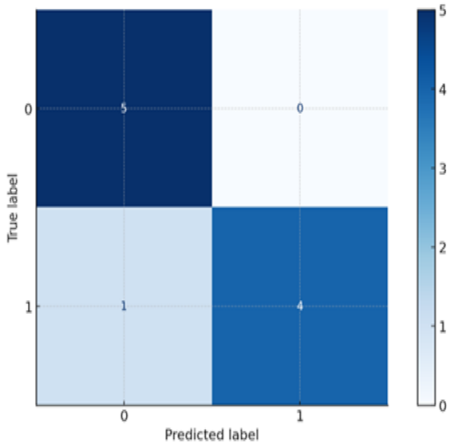

Figure 6: The confusion matrix

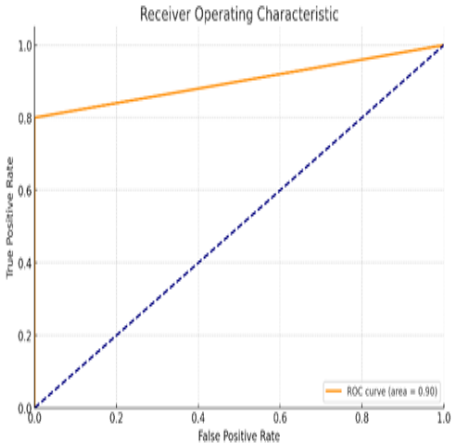

Figure 7: ROC curve

WPD enhances the input features in that it gives precise frequency details. On the other hand, the Multiscale CNN operates these features at different scales, thus improving its ability to learn complex patterns that enhance the classification result. The experiments also show that standard CNN is suboptimal as it does not reproduce the results even when WPD is applied. This implies that the multiscale framework of using different kernel sizes to obtain features of various scales is essential. Generally, these results demonstrate that WPD is beneficial in detecting MI from ECG signals, so it is for Multiscale CNN.

6.2 Generalizable capabilities

The generalization capabilities of a model are critical in assessing its robustness and applicability across various subjects and datasets. This study used independent dataset validation to determine the model's predictive accuracy on new cases not part of the training dataset. The independent dataset used for validation differed from the one used in the training process, and there was no intersection between these two datasets. To check this, validation was conducted using the k-fold cross-validation method, where the data set was split into five sets (k=5) such that subjects were distributed across all the five data splits. It contributes to mitigating inter-subject variability, a significant issue in motor imagery tasks, as different patterns of ECG signals can influence a model. The performance was almost steady across the folds, which shows the ability of the model to perform well for new subjects in the dataset.

However, exercising the model with a validation technique other than K-fold cross-validation would be more meaningful, for instance, testing the model on a new data set not used in the training phase. A validation approach with an independent test set would also test the model's ability to generalize to highly different conditions if the independent dataset differs in signal quality, subject characteristics, or data acquisition techniques. For instance, using an exter-

Table 2: Comparison with traditional methods

Metric	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Recall
SVM	0.85	0.83	0.86	0.84	0.88	0.88
Random Forest	0.87	0.84	0.88	0.86	0.9	0.9
Multiscale CNN	0.92	0.89	0.93	0.91	0.95	0.95
MCC	98.17	-	-	-	-	-

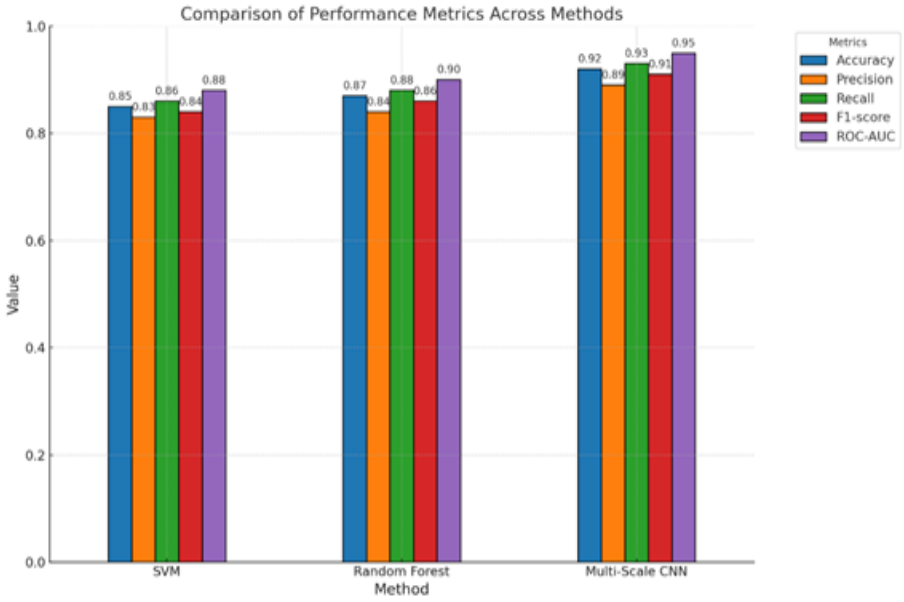

Figure 8: Comparison with traditional methods

nal set we obtain from a different recording protocol would help determine how much the proposed model hampers or inspires adaptability for different data characteristics. If loss occurs in these cases, it may show the aspects in which the model has to be optimized to be generalized better.

To strengthen the evaluation, it is recommended to expand the main parameters, including accuracy, precision, and relative, especially in cases of imbalance in collection. It should be noted that using values such as specificity or MCC will give a better picture of the effectiveness of the examined model. Although MCC was not used in the current study, it is a valuable metric considering true positives, false positives, and false negatives, thus offering insight into the model's performance in imbalanced conditions. Future work could incorporate these additional metrics and further investigate techniques such as domain adaptation to enhance the model's applicability across different data sources.

6.3 Directions for future work

While the proposed methodology has made considerable strides in motor imagery detection research, there are several avenues of inquiry forward that would further enhance and generalize these findings:

6.3.1 Exploration of alternative wavelet functions:

The Daubechies 4 dB4 wavelet was suitable for this work; some studies on other wavelet functions and their impact on the features extracted would add more value. Other wavelet functions capture unique characteristics in the signal that could lead to further improvements in classification accuracy.

6.3.2 Multi-modal data fusion:

Such ECG signals can be combined with other physiological signals, such as EEG and EMG, further to improve the robustness and accuracy of motor imagery detection [17]. Multi-modal fusion methods combine complementary information from different sources to describe a motor imaginary event completely.

6.3.3 Advanced deep learning architectures:

Research about advanced deep learning architectures based on RNN and attention mechanisms can achieve even better

performance for motor imagery detection [18]. These architectures have confounders of temporal dependencies and contextual information that could improve the detection of the subtle pattern of ECG signals.

6.3.4 Real-time implementation:

Based on the proposed methodology, designing real-time systems for motor imagery detection must move the work toward a practical application. Implementing the model in time-real environmental systems and testing its performance under dynamic conditions becomes crucial for deploying the technology in neuroprosthetic devices and BCI systems.

6.3.5 Large-scale validation:

Further large-scale validation is required to generalize the findings and check the robustness of the proposed approach with datasets and subjects under study. The model will be tested experimentally across different populations, tasks, and recording conditions to estimate its reliability and scalability.

6.3.6 Transfer learning and domain adaptation:

If the model is adapted to different domains and tasks using transfer learning, it can be flexible. Domain adaptation methods may alter the model's capability towards generalizing new data, at least with its reusability on minimal retraining.

6.3.7 User-centric design:

Provisions for user feedback in the motor imagery detection system and the development of user-centric interfaces will likely improve its usability and acceptance [19]. Knowledge of the desires and preferences of the end-user, such as a person with a motor impairment, may guide the development of more intuitive and effective BCI systems.

6.3.8 Ethical considerations and data privacy:

Ethical considerations and data privacy are paramount in collecting, processing, and using physiological signals. Frameworks on ethical data handling and compliance with privacy regulations will be essential to ensure the responsible deployment of technologies for motor imagery detection [20].

7 Conclusion

In conclusion, the ablation study confirms that Wavelet Packet Decomposition and Multiscale CNN are integral components of the proposed method. WPD provides a rich, multi-scale representation of the ECG signals, which, when processed by a Multiscale CNN, leads to superior motor imagery classification performance. Removing either component significantly declines model accuracy, illustrating their combined importance in the overall framework. This research presents a new motor imagery detection scheme from ECG signals using Wavelet Packet Decomposition and Multiscale Convolutional Neural Networks. The methodology indeed enhances the classification accuracy to a large extent; hence, it needs no explicit mention. The results also indicate that an ECG signal is feasible in motor imagery detection as a noninvasive and easily accessed technique for developing neuroprosthetic devices and BCI systems. These contributions help support further studies in this area of research, which has enormous room for further improvement and exploration. On the way ahead, addressing the suggested directions for future work will continuously advance the field and, eventually, achieve more effective and dependable technologies related to motor imagery detection.

This study's methodology will be open-sourced to ensure reproducibility for other research groups to extend and continue their collaboration in biomedical signal processing and brain-computer interface. In the future, with further research in this area, the full potential of MI detection using the ECG signal can be achieved to benefit people suffering from motor impairments and progress in neuroprosthetic/BCI capabilities.

Acknowledgment

I am grateful to the University of Basrah for providing the resources and environment needed to complete this research. I also want to thank the Computer Science Members for their collaborative spirit and helpful discussions, which contributed significantly to the ideas presented here.

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Online Criminal Behavior Recognition Based on CNNH and MCNN-LSTM

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Keywords: anonymous networks, traffic segmentation, convolutional neural networks, online crime, long short-term memory networks

Received: November 10, 2024

*In light of the proliferation of cybercrimes, the effective identification and mitigation of such online criminal activities has emerged as a significant challenge within the domain of network security. Therefore, this study introduces dilated convolution technology, self-attention mechanism, convolutional neural network and long short-term memory network, and proposes an overlapping traffic recognition model based on improved convolutional neural network and an online crime recognition model with long short-term memory network. In the traffic segmentation model test, the recall rate, F1 value, and error rate of the model under normal traffic conditions were 91.43%, 93.46%, and 92.43%, respectively. The error rate was 4.15%. The accuracy of the online crime recognition model for malware propagation and illegal transactions was 96.54% and 92.87% respectively. In the concept drift test, when the training time and test time interval was 60 days, the accuracy of the model was 48.67% higher than that of the long short-term memory network. Compared with the mainstream framework and traditional methods, its accuracy in high traffic scenarios was 94.78%, the error rate was 3.89%, and the P-*value *was < 0.05. In the final simulation test, the model could effectively identify illegal software transactions. The results show that the proposed model has high accuracy and strong generalization ability in identifying overlapping traffic and website fingerprint crimes, and effectively improves the detection ability of criminal activities in anonymous networks.*

Povzetek: Predstavljen je model za prepoznavanje spletnega kriminala, ki temelji na konvolucijskih in LSTM nevronskih mrežah in z uporabo tehnologije razredčene konvolucije in mehanizma samo-pozornosti dosega visoko točnost pri segmentaciji prometa in prepoznavanju spletnih kaznivih dejanj. Učinkovito izboljšuje zaznavanje kriminalnih aktivnosti v anonimnih omrežjih.

1 Introduction

With the rapid development of Internet technology, the increasing complexity and openness of cyberspace have brought unprecedented opportunities and challenges to society [1]. The emergence and popularization of anonymous networks provide an important guarantee for users' privacy protection in the network. However, it also makes some wrongdoers utilize anonymous networks to engage in various criminalactivities, among which the anonymous communication system represented by the onion router (Tor) is particularly typical [2]. Tor network realizes the high anonymity of user identity and communication content through multi-layer encryption and node forwarding techniques, which is widely used for legitimate purposes such as protecting user privacy and preventing network surveillance. However, the anonymity of Tor network is also used by some criminals to circumvent legal supervision and become a hotbed for cybercriminal activities, such as illegal trading, malware distribution, hacking and other behaviors [3]. In this context, applying overlapping traffic segmentation and website fingerprinting (WF) technology to collect potential criminal evidence and detect abnormal behavior in an early stage in order to identify and combat online criminal behavior in anonymous networks has become a key issue that needs to be addressed urgently. At the same time, the industry's research on anonymous network traffic analysis and criminal behavior identification is also deepening and developing. Wang Y et al. proposed a deep learning-based intrusion detection system SMSO-CNN to address the security risks and privacy issues caused by the transmission of large amounts of data in wireless networks. The system combined the spider monkey swarm optimization algorithm and CNN to improve the ability to identify network attacks. The results showed that the system was superior to LSTM and other methods in terms of accuracy [4]. Gu X et al. proposed an online defense strategy based on non-targeted adversarial patches to address the limitations of existing WF attack defense methods in practical applications. Experiments indicated that the model achieved 95.50% defense accuracy and 12.57% time overhead in real-time traffic [5]. To address the problem of high dimensionality of cybercrime data, Rawat R et al. proposed a feature selection method based on multi-objective evolutionary algorithm (MOEA) and combined it with NSGA-II to reduce data dimensionality and identify the most relevant features. The experimental results indicated that this method effectively improves the efficiency of data processing [6]. Xian K proposed an

improved WF fingerprint recognition algorithm to solve the problem of identifying encrypted traffic in virtual private networks. Moreover, it combined it with an optimized capsule neural network model CapsNet to classify encrypted traffic. The research results showed that this method was superior to the random forest algorithm in terms of recognition accuracy and convergence speed, with a recognition rate of 99.98% [7]. Milad N et al. proposed a blind adversarial perturbation algorithm to address the problem that traffic analysis technology based on deep neural networks (DNN) was vulnerable to adversarial perturbation attacks. By remapping functions to create adversarial perturbations independent of network connections, the algorithm was applied to real-time anonymous network traffic analysis to defeat WF identification and traffic association classifiers. The experimental results indicated that this method was applicable to a variety of traffic classifier types. The robustness test of existing countermeasures performed poorly [8].

Because of their superior 2D data processing capabilities, convolutional neural networks (CNNs) are frequently utilized in image categorization and target recognition applications. Yesodha K et al. suggested a novel intrusion detection system incorporating CNN, fuzzy temporal rules, and an artificial bee colony optimization algorithm for the security vulnerability problem in wireless sensor network communication with the goal of improving the classifier's performance. Based on experimental assessments, the model performs better in terms of increased accuracy and decreased false alarm rate than popular classification algorithms like long short-term memory (LSTM) [9]. A CNN intrusion detection technique based on data imbalance was presented by Gan B et al. to address the hazards to network security brought on by recurrent network intrusions. The findings revealed that, with an implementation time of 1.42 seconds, the method attained an average accuracy of 98.73% in binary and multi-classification identification [10]. An intelligent prediction technique for security performance was suggested by Xu L et al. to address security concerns in mobile IoT healthcare networks. To increase the CNN model's adaptability to nonlinear medical large data, the study combined a four-branch beginning block with a four-layer convolution. The results indicated that the intelligent algorithm improved the security performance prediction accuracy by 20% and had better prediction performance [11]. Yan F. et al. addressed the issue of inadequate training samples and sample class imbalance in intrusion detection systems by proposing an intrusion detection system based on migration learning and integrated learning. The two fundamental learning models that were selected were Xception and Inception. A tree-structured estimator was used to tune the hyperparameters [12]. Finally, the study summarizes the research areas, indicator test results, and limitations of the above literature review. The results are shown in Table 1 below.

Table 1: Literature summary table

Study	Methodology	Performance Metric	Shortcomings
Wang Y et al. [4]	Intrusion detection system based on SMSO-CNN	Higher accuracy than LSTM and nearest neighbor algorithms	Not designed for anonymous network traffic, struggles with overlapping traffic
Gu X et al. [5]	Fingerprint defense strategy of online website based on Grad-CAM	95.50% defense accuracy, 12.57% time overhead	Focuses on defense tasks, does not address abnormal behavior recognition in anonymous networks
Rawat R et al. [6]	Feature selection method based on MOEA combined with NSGA-II for dimensionality reduction	Effectively improves data processing efficiency	Focused on feature selection, lacks real-time traffic analysis
Xian K et al. [7]	Optimized fingerprint recognition for encrypted traffic based on CapsNet	SSL VPN traffic recognition rate of 99.98%, recall rate of 99.98%	Effective for encrypted traffic classification but lacks ability to handle complex anonymous traffic patterns
Milad N et al. [8]	Blind adversarial perturbation algorithm to defeat DNN-based traffic analysis methods	Demonstrated high effectiveness across multiple traffic classifiers	Robustness testing performs poorly
Yesodha K et al. [9]	Intrusion detection system based on FT-ABC-CNN	Low false alarm rate, higher classification accuracy than long short-term memory networks	Limited to generic network features, cannot handle overlapping traffic patterns
Gan B et al. [10]	Intrusion detection method based on CNN-IDMDI	Average binary and multi-class accuracy of 98.73%	Lacks temporal feature extraction, struggles with dynamic and complex behaviors
Xu L et al. [11]	Improved CNN for IoT-enabled security performance prediction	Improves prediction accuracy by 20%	Focused on IoT, does not consider dynamic features of anonymous networks

Yan F et al. [12]	Intrusion detection system based on TL-CNN-IDS	Significantly improves accuracy	Limited datasets, does not address overlapping traffic or anonymous network issues

Combined with Table 1, most studies have some shortcomings while improving the ability of traffic classification and behavior recognition. First, the majority of extant methods prioritize comprehensive network traffic monitoring, yet they are deficient in their capacity to discern intricate and clandestine criminal activities. This is particularly problematic in anonymous network environments, where traditional rule-based matching methods are challenging to implement effectively to detect anomalous behaviors indicative of specific criminal activities. Second, many traffic analysis methods often have a high false alarm rate in practical applications, which makes it difficult for law enforcement agencies to respond quickly when faced with massive alarm information. In addition, these methods have low computational efficiency and are difficult to meet the requirements of real-time monitoring of large-scale network traffic. In view of this, this study introduces the hollow convolution technology in CNN and proposes a Tor overlapping traffic segmentation model based on the hollow convolution convolutional neural network (CNNH). At the same time, combining the attention mechanism, CNN, and LSTM, an online criminal behavior recognition model based on multi-core convolutional neural networks and long short-term memory networks (MCNN-LSTM) is proposed. The model analyzes network traffic characteristics, accurately identifies the websites visited by users, and effectively identifies anomalous network behaviors related to criminal activities, becoming a powerful auxiliary tool for online crime investigation.

The main contributions of the study are as follows: First, the MCNN-LSTM model based on the combination of multi-core convolution and LSTM network is proposed. By using multi-module collaborative optimization, the modeling capabilities of spatial features and time series features are integrated to improve the theoretical framework and method design of network traffic anomaly detection. Second, the self-attention mechanism (SAM) is introduced into the model architecture, which can dynamically focus on key features and improve the model's adaptability to dynamic environments. Finally, a multi-scale feature extraction method is proposed to capture multi-scale spatial features based on the multi-core convolution module.

2 Methods and materials

2.1 Online crime and its challenge

Online criminals often use the anonymity, privacy protection and global characteristics of the Internet to carry out various illegal activities, including illegal gambling, online transactions, money laundering, malware propagation, etc. Studies have shown that the economic losses caused by cybercrime worldwide each year have reached hundreds of billions of dollars, which has brought a huge burden to the global economy [13]. The diversity and complexity of cybercrime make traditional legal supervision and law enforcement methods face huge challenges in dealing with these behaviors.

Among online crimes, online gambling is a relatively common type. Criminals attract users to participate in online gambling activities by setting up and operating illegal gambling websites. These websites usually rely on anonymous networks, such as the Tor network or cryptocurrency payments, which greatly improves their concealment and evades legal supervision. This makes it difficult for law enforcement agencies to track and collect evidence, making it difficult to effectively combat these criminal activities. Online prostitution is also an illegal activity carried out using the Internet. Criminals usually promote and trade through dark web platforms to avoid tracking. In addition, illegal transactions are also an important aspect of online criminal activities. Criminal's trade prohibited items such as drugs, weapons, and counterfeit goods in anonymous markets such as the dark web. Such markets often rely on complex encryption technology and anonymous payment methods to conduct transactions, making it extremely difficult for law enforcement agencies to investigate. Another important form of online crime is the spread of malware. Malware includes ransomware, phishing software, etc., which can be spread through various network channels and pose a serious threat to individuals, enterprises and even government agencies. The spread of malware can not only steal personal privacy information, but also lead to the loss of core corporate data, and in serious cases, even endanger national security. Every year, the number of data leaks caused by malware is huge, and the economic losses caused are difficult to estimate [14]. In addition, with the popularization of IoT technology, cyber attacks on smart devices are also on the rise, further expanding the scope of online criminal activities.

Faced with these challenges, traditional legal and law enforcement methods are unable to cope with the high concealment and transnational nature of online crimes. Researchers and law enforcement agencies have begun to rely on advanced technical means, especially recognition algorithms based on network traffic analysis and deep learning. Through these technologies, researchers can extract useful features from massive amounts of network data to identify and track criminal behavior. In recent years, more and more research has been devoted to improving traffic analysis methods to improve the ability to detect complex cybercrime, especially crimes in anonymous networks. In the future, with the further development of technology, more intelligent detection systems for online criminal behavior will be widely used to better cope with the growing network threats.

Online crime identification is the process of locating and assessing possible illegal activity, such as online gambling, malware distribution, and illegal transactions, by analyzing network traffic, user behavior patterns, and data characteristics. Unlike traditional network traffic analysis, online crime identification focuses more on the complex characteristics of criminal behavior hidden in anonymous networks, often involving protocol abuse, encrypted data streams, and anomalous behavior patterns. Anomalous network behavior usually manifests itself in the form of anomalous network traffic patterns, including but not limited to the following. On the Tor network, high-frequency, short-duration access patterns may reflect scanning attacks. Abnormal packet intervals or excessively large packet sizes may indicate covert channel communications. Sudden changes in traffic characteristics may indicate malware activity. In this context, this study will explore a network traffic analysis method based on deep learning and explore its application potential in identifying anomalous network behavior in the early stage of online crimes.

2.2 CNN-based model construction for tor overlapping traffic segmentation

With the development of anonymous communication technology, Tor network is widely used for both legal and criminalactivities due to its strong anonymity and privacy protection [15]. Tor achieves anonymity in communications by dividing user communications into multiple data packets, transmitting them through multiple relay nodes, and encrypting and decrypting the data packets. The high privacy of anonymous networks makes them an important tool for legitimate users to protect their privacy, but they also provide shelter for various criminalactivities, such as online gambling, online prostitution, and illegal transactions. These crimes not only cause great social harm, but also bring great challenges to law enforcement agencies in identification and tracking. At the same time, this anonymity also makes traffic analysis and identification more difficult, especially in the case of overlapping traffic. Overlapping traffic segmentation refers to the technique of decoupling and segmenting the traffic when the communication data of multiple users are transmitted simultaneously over the same communication link in an anonymous network environment. In contrast to the broader approach of network traffic analysis, the concept of overlapping traffic segmentation entails the identification of the traffic aliasing relationship between disparate users and the extraction of characteristic information from the traffic of particular users. This facilitates the detection of potential abnormal behavior. The flow of traditional overlapping traffic segmentation is shown in the following Figure 1.

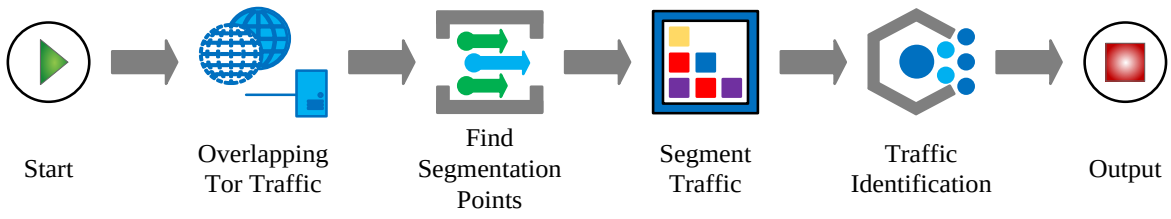


Figure 1: The basic process of overlapping traffic segmentation

As shown in Figure 1, first identify the key segmentation points in the traffic, and use these segmentation points to segment the traffic and extract feature points related to specific behavior patterns. Then, the segmented traffic segments are recognized and classified, and finally further processing is performed based on the recognition results. CNN has a strong feature extraction capability and is suitable for handling overlapping traffic in network traffic. Online criminal activities are often accompanied by complex network traffic patterns that may overlap with normal traffic, increasing the difficulty of identification. By using convolution kernels to extract local features from input traffic, CNN can effectively separate and identify abnormal behavior patterns in overlapping traffic, thereby helping to detect potential criminal activities, such as suspicious transaction requests or abnormal data packet transmissions. Therefore, the study will construct overlapping traffic segmentation model based on CNN. CNN applies convolutional kernel to extract local features by sliding window approach, the calculation is shown in Equation (1) [16].

$$Y_{i,j} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} X_{behavior,(i+m),(j+n)} W_{m,n} + b \quad (1)$$

In Equation (1), $Y_{i,j}$ represents the value of the output feature map at position (i, j). $X_{behavior,(i+m),(j+n)}$ is the element in the input feature map. $W_{m,n}$ represents the weight matrix element of the convolution kernel. The training model can automatically adjust the weight to better capture specific behavior features. b is the bias term. M and N denote the height and width of the convolution kernel. Equation (2) illustrates why the rectified linear unit (ReLU), which is easy to understand, quick to compute, and capable of handling deep networks, is chosen as the activation function.

$$f(x) = max(0, x) \quad (2)$$

In Equation (2), x denotes the value input to the activation function after the convolution operation. In the next pooling stage, the expression is shownin Equation (3) [17].

$$P = \max_{window}(X_{behavior\_feature}) \tag{3}$$

In Equation (3), P is the maximum value of the pooling window. $X_{behavior\_feature}$ is the element of the input feature map, which includes behavior features extracted from network traffic such as transmission frequency and directional features. Through downsampling, the pooling procedure shrinks the FM's size, lowering computational cost and enhancing the model's resilience. Finally, the fully connected layer (FCL) expression is shown in Equation (4) [18].

$$\begin{cases} z = Wz' + b \\ z' = \left[z'_{trade}, z'_{malware}, z'_{anomaly} \right] \end{cases} \tag{4}$$

In Equation (4), z' is the input high-dimensional feature vector, and W is the weight matrix of the fully connected layer. z' contains a combination of multiple behavioral features, and z'_{trade}, $z'_{malware}$, and $z'_{anomaly}$ represent features related to illegal transactions, malware propagation, and other abnormal behaviors, respectively. Among the most often utilized loss functions in classification problems is the cross-entropy loss function. Equation (5) illustrates its expression by calculating the difference between the probability distribution (PD) of the real labels and the PD predicted by the model.

$$L = -\sum_{i=1}^{N} w_{behavior\_feature}(y_i \log(\hat{y}_i)) \tag{5}$$

In Equation (5), L is the loss value. $w_{behavior\_feature}$ represents the weight factor related to the behavior characteristics. N represents the number of samples, y_i is the true label, and i represents the actual category corresponding to the sample, that is, whether it is an illegal activity. $\hat{y}_i$ is the probability distribution predicted by the model. By adding the weight factor of the behavior characteristics, the model can more effectively focus on the characteristics related to the criminal behavior, thereby improving the recognition effect of the model in specific criminal behavior scenarios.

Due to the highly encrypted and complex time series characteristics of Tor traffic, the study introduces the hollow convolution technique, by introducing cavities in the convolution kernel. That is, extending the receptive field without adding more parameters by adding gaps between the convolution kernel's parts. Hollow convolution (also known as expanded convolution) is a technique that expands the receptive field by inserting holes in the convolution kernel, capturing a wider range of features without increasing the number of parameters. This method helps the model handle long-range dependencies while maintaining computational efficiency, as shown in Figure 2.

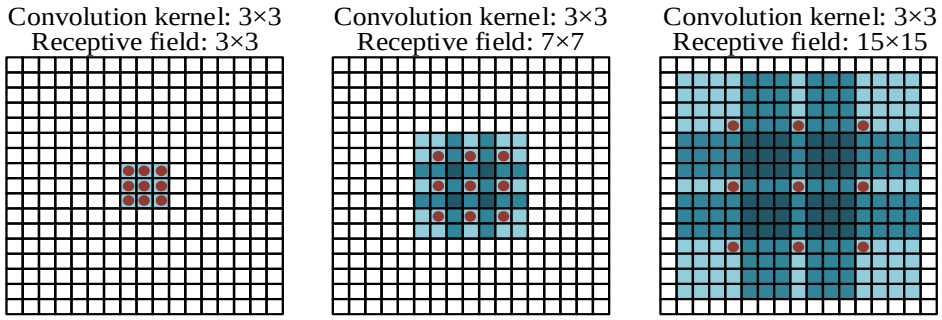


Figure 2: Multi-scale feature extraction using dilated convolution

Figure 2(a), (b), and (c) represent the convolutional kernel arrangement with convolutional expansion rate of 1, 2, and 4, respectively. In Figure 2(a), when the convolutional expansion rate is 1, the convolutional kernel size is 3×3, which is the same as the conventional convolutional kernel, and the sensory field only covers the local area. In Figure 2(b) with a convolution expansion rate of 2, the convolution kernel sense field expands to 7×7, but the actual parameters remain 3×3. In Figure 2(c) with a convolution expansion rate of 4, the sense field further expands to 15×15, and the number of parameters remains the same. Null convolution can effectively extract multi-scale information and remote-dependent features without increasing the computational complexity, and is suitable for processing complex features in Tor traffic.

In the rest of the model, batch normalization is first introduced after each convolutional layer to accelerate convergence and improve generalization. Second, a larger range of contextual information is captured by expanding the sensory field by the application of null convolution. Moreover, to prevent overfitting, a Dropout layer is introduced to enhance model robustness. Furthermore, to better handle the complex aspects of Tor traffic, a deep network structure is built by stacking numerous convolutional, pooling, and FCLs. Therefore, the structure of the overlapping traffic segmentation model of CNNH is shown in Figure 3 below.

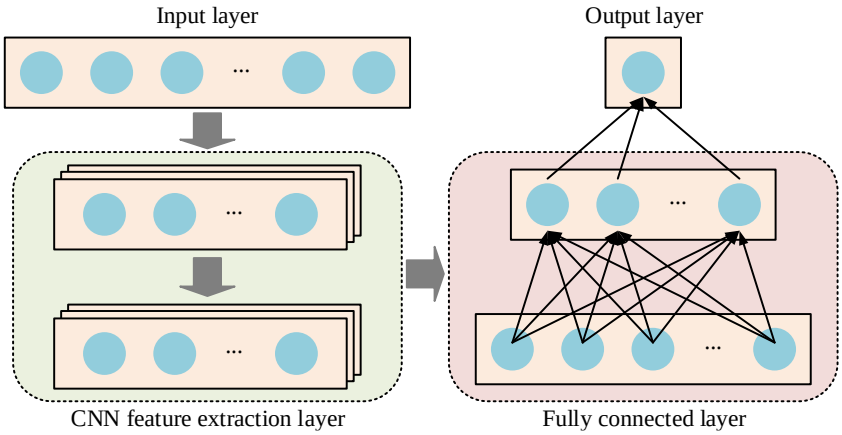


Figure 3: Overlapping traffic segmentation model based on CNNH

As shown in Figure 3, the process of the CNNH overlapping traffic segmentation model consists of four parts. First, the input layer receives the original Tor traffic data and passes it to the CNN layer. The CNN layer extracts representative features from the input traffic through a series of convolution operations and pooling operations, including network behavior features such as packet size, transmission time interval, and transmission frequency. These extracted features are then passed to the FCL, where the features are further comprehensively analyzed to generate a high-dimensional feature vector. Finally, the output layer completes the prediction and classification of the traffic segmentation results based on the output of the FCL, helping the model distinguish between legitimate traffic and potential criminal behavior. To facilitate understanding of the specific implementation of the CNNH model, the pseudo code is given below, as shown in Figure 4.

```
# Pseudocode for CNNH Model
# Pseudocode for CNNH Model
# Input: Network traffic data (X), labels (Y)
# Output: Predicted labels (Y_hat)

# Step 1: Data Preprocessing
X_preprocessed = preprocess_data(X)  # Normalize and extract features

# Step 2: Dilated Convolution (Hollow Convolution) Module
def DilatedCNN_Module(X):
    Conv1 = Conv2D(filters=32, kernel_size=(3, 3), dilation_rate=1, activation='relu')(X)
    Conv2 = Conv2D(filters=64, kernel_size=(3, 3), dilation_rate=2, activation='relu')(Conv1)
    Conv3 = Conv2D(filters=128, kernel_size=(3, 3), dilation_rate=4, activation='relu')(Conv2)
    PooledFeatures = MaxPooling2D(pool_size=(2, 2))(Conv3)
    return PooledFeatures

X_dilated = DilatedCNN_Module(X_preprocessed)

# Step 3: Fully Connected Layers for Classification
def ClassificationHead(X):
    Dense1 = Dense(units=64, activation='relu')(X)
    Output = Dense(units=num_classes, activation='softmax')(Dense1)
    return Output

Y_hat = ClassificationHead(X_dilated)

# Step 4: Model Training
model = compile_model(optimizer='adam', loss='categorical_crossentropy')
model.fit(X_preprocessed, Y, epochs=50, batch_size=32)
```

Figure 4: Overlapping traffic segmentation model based on CNNH

The pseudo code in Figure 4 shows the workflow of the CNNH model in complex network traffic feature extraction. The model effectively expands the receptive field through the hole convolution module. Therefore, it can reduce information loss while maintaining the integrity of spatial features.

2.3 Research on online criminal behavior recognition model based on LSTM and CNN

CNN for traffic segmentation, although excellent in spatial feature extraction, still suffers from recognition limitations when confronted with time-series features in Tor traffic. In contrast, LSTM, as a recurrent neural network that excels in processing sequence data, is suitable for the field of network traffic analysis due to its powerful modeling capability of time series features [19]. In online criminal behaviors, such as cyber attacks or illegal transactions, specific time patterns are often shown, such as persistent illegal access attempts or regular small-amount fund transfers. By analyzing the time series features in network traffic, LSTM can identify the regularity of these criminal behaviors and provide support for crime prevention by predicting future behavior trends. Therefore, the study will try to combine CNN and LSTM and introduce the SAM to extract and classify important features.

In the overall process design, the input data is first processed through a data encoding module to convert the raw data into a form suitable for model input. Then, it is passed through the SAM module in order to enhance the attention to the key features. Then, CNN and LSTM modules perform feature extraction and time series analysis on the data processed by the attention mechanism, to capture behavioral patterns that recur over long periods of time. Finally, the model outputs the recognition results to realize the recognition of WF. In the data encoding module, the training data is shown in Equation (6).

$$\begin{cases} T = \{(X_1, G_1), (X_2, G_2), ..., (X_n, G_n)\} \\ X = (1, -1, 1, -1, ..., 1) \end{cases} \quad (6)$$

In Equation (6), T denotes the training data set. X_n and G_n denote the n th traffic instance and website class label, respectively. One-Hot encoding, a popular encoding technique in neural network multi-classification tasks, is crucial for guaranteeing the classification model's accuracy, preventing label misrepresentation, and increasing computational efficiency. Therefore, One-Hot state bits are used for encoding. Further, in the SAM module, the correlation matrix of the input sequence is first calculated as shown in Equation (7) [20].

$$\begin{cases} V = X \cdot W_v \\ K = X \cdot W_k \\ Q = X \cdot W_q \end{cases} \quad (7)$$

In Equation (7), V , K , Q denote the value, key, and query matrices, respectively. W_v , W_k , and W_q all denote the initial weight matrices, which correspond to the value, key, and query weight matrices, respectively. These matrices project the input sequences into different vector spaces for subsequent computation of the attention scores. The attention score is shown in Equation (8).

$$attention(a, V) = \sum_{j=1}^{j=n} a_i \cdot v_j i \quad (8)$$

In Equation (8), a_i denotes the i th attention weight. v_j is the element at the j th position in the value vector V . Thus, Figure 5 shows a schematized version of the SAM structure.

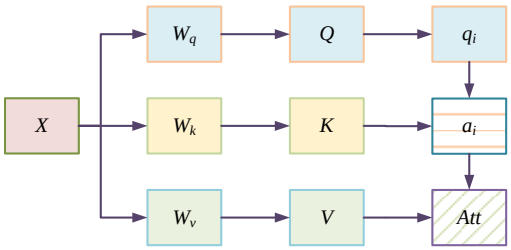


Figure 5: Self attention mechanism layer structure

In Figure 5, the input sequence X is first converted to value matrix V , key matrix K , and query matrix Q through three weight matrices W_v , W_k , and W_q , respectively. Then, the Q and K calculate the correlation through dot-product operation, and the result is inputted into the Softmax function (SF) to generate the attention weights a_i after scaling. These attention weights are used to weight the corresponding elements in the V elements, and finally the weighted value matrix is passed through a summation operation to obtain the output. By using this approach, the model can dynamically concentrate on important features according to how important each segment of the input sequence is. This successfully boosts the model's performance when processing complex data and improves its capacity to capture vital information. Finally, in the CNN and LSTM module, the resulting feature sequence is spliced into a two-dimensional feature matrix. Then the one-dimensional maximum pooling layer (PL) is connected for data dimensionality reduction processing, and the expression is shown in Equation (9).

$$Y_{i,h=5}^{l} = \max(Z_{j-1}^{l}, Z_{j}^{l}, Z_{j+1}^{l}, Z_{j+2}^{l}) \quad (9)$$

In Equation (9), $Y_{i,h=5}^{l}$ then denotes the result of the pooling operation via the convolution kernel of 5. Z_{j}^{l} , Z_{j+2}^{l} , and Z_{j+2}^{l} all denote the neighboring feature values in the previous layer of l . Subsequently, the extracted spatial features are fused as shown in Equation (10).

$$F_j^l = concat(Y_{i,h=3}^{l}, Y_{i,h=4}^{l}, Y_{i,h=5}^{l}) \quad (10)$$

In Equation (10), F_j^l denotes the fused features after convolution and pooling. $Y_{i,h=3}^{l}$, $Y_{i,h=4}^{l}$, and $Y_{i,h=5}^{l}$ denote

the i th output of the pooling of the l th layer with convolution kernel size 3, 4, and 5, respectively. Equation (11) illustrates how the data is put into the LSTM to extract the temporal features once the fusion is finished.

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b) \quad (11)$$

In Equation (11), h_t and h_{t-1} represent the hidden states of the current time step and the previous time step, respectively, that is, the contextual information of the behavioral features at the current moment. For identifying criminal behavior, the information of the previous time step, such as the occurrence of certain abnormal behaviors at the previous moment, can help predict whether the behavior at the current moment is abnormal. x_t represents the input features of the current time step, and W_h represents the weight matrix of the hidden state, which can learn how to transfer the criminal behavior features of the previous moment to the current moment. W_x is the weight matrix of the input features, which is used to weight the input features of the current time step. These weights can learn the importance of different behavioral features in predicting criminal behavior. b is the bias term, and σ is the activation function. By introducing nonlinearity, the model can capture complex behavioral patterns. Finally, the model further fuses spatial features, temporal features and behavioral features to form a unified feature representation. Specifically, spatial features are extracted through the convolution layer, temporal features are captured through the LSTM layer, and behavioral features are extracted based on high-risk behavior patterns in traffic. The fused feature representation is shown in Equation (12).

$$z = \alpha z_{spatial} + \beta z_{temporal} + \gamma z_{behavioral} \quad (12)$$

In Equation (12), $z_{spatial}$ represents the spatial features extracted by the convolution layer, which can help identify local anomalies in network traffic. $z_{temporal}$ represents the temporal features extracted by the LSTM layer, which captures recurring patterns in the time dimension, especially high-frequency packet transmission behaviors. $z_{behavioral}$ represents the high-level features obtained by the behavioral feature extraction mechanism, which reflects specific behavioral patterns such as malware propagation and illegal transactions. α , β , and γ are all weighting factors. The weights are adjusted according to the importance of different features to ensure the sensitivity of the model to specific behavioral patterns. Therefore, the improved CNN-LSTM structure is shown in Figure 6 below.

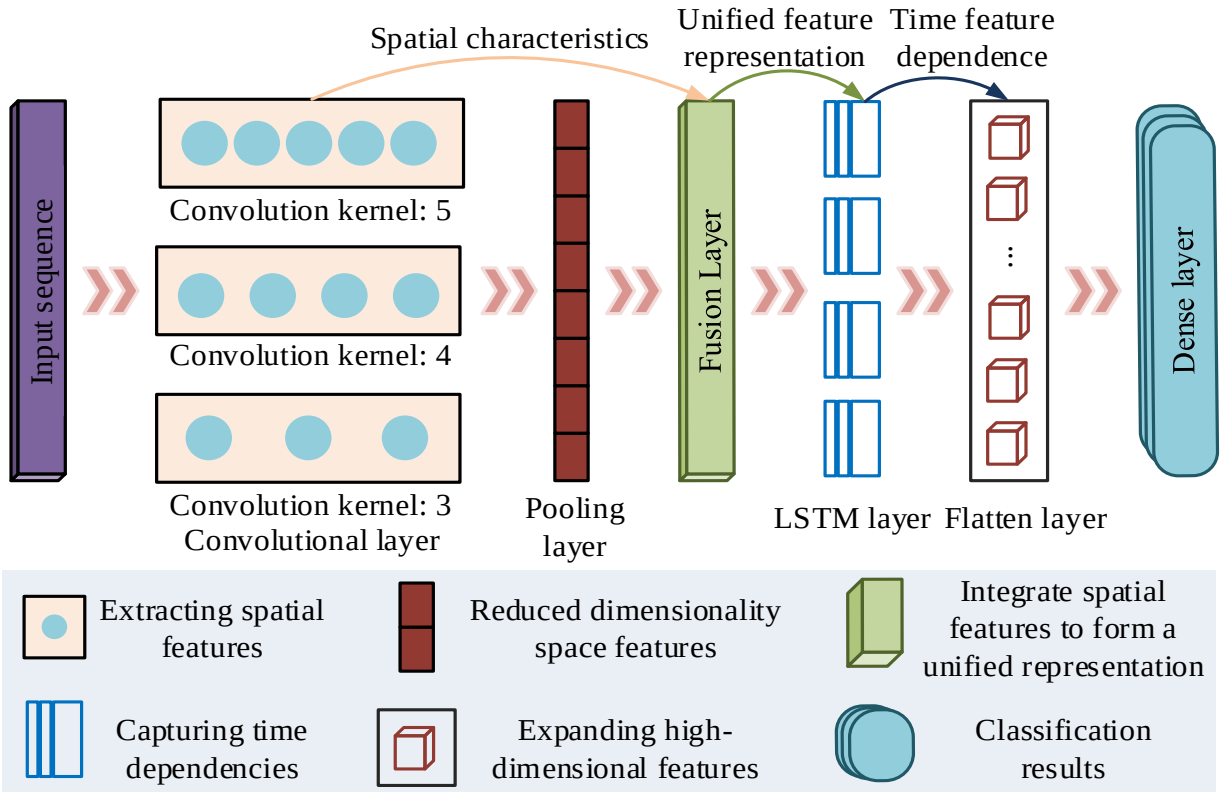


Figure 6: The structure and temporal feature fusion of the MCNN-LSTM Model

In Figure 6, first, the input sequence passes through multiple convolutional layers, each with a different convolutional kernel size to capture different scale features in the input data. Subsequently, a PL is used to downsample the convolved FMs, so decreasing their size and, consequently, the computational complexity. Then, the multi-scale features are integrated through a fusion layer to form a unified feature representation, helping the model capture more comprehensive traffic information. Immediately afterward, these features are passed to the LSTM layer. The LSTM layer specializes in processing time-series data and is able to capture long-range dependencies in the data. Subsequently, the high-dimensional features output from the LSTM layer are expanded into one-dimensional vectors through the Flatten layer. Finally, the output of the classification or regression task is carried out through the FCL, thereby identifying potential criminal behavior in network traffic. Therefore, according to the above calculations, the online criminal behavior recognition process based on MCNN-LSTM is shown in Figure 7.

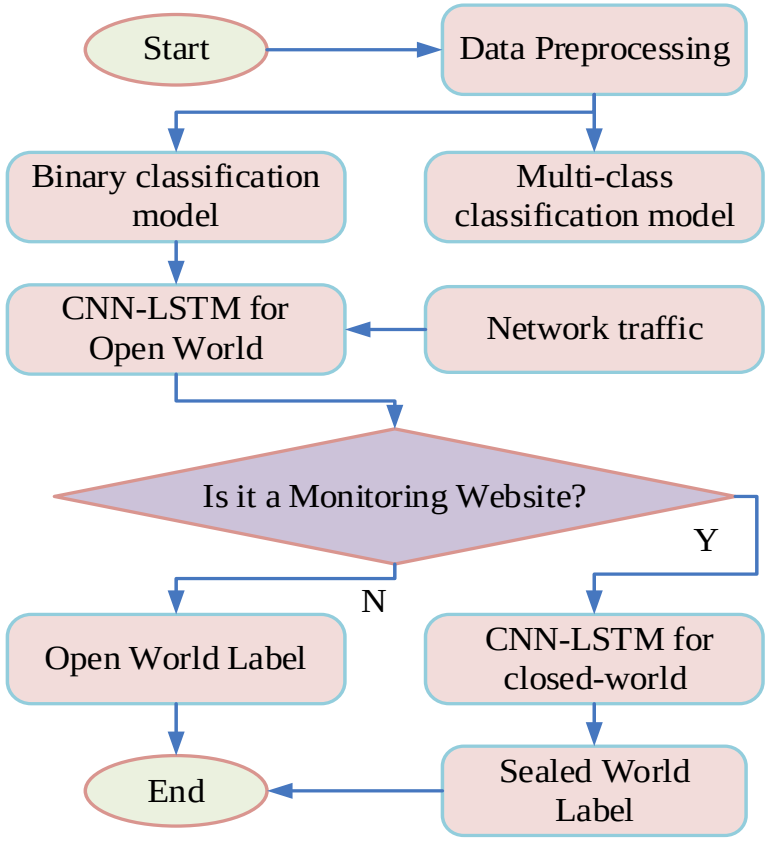


Figure 7: Online criminal behavior identification process

As shown in Figure 7, first, during the training phase, the preservation model is trained using the binary and multi-classification datasets created from the network traffic data, respectively. In the recognition phase, the input network traffic is first processed by the open-world MCNN-LSTM to determine whether it is labeled in the accusation domain. If the traffic belongs to the accusation domain, it enters the open-world label processing and is recognized using the closed-world MCNN-LSTM. If it does not belong to the accusation domain, it enters the closed-world labeling processing. Through the staged processing, the model is able to process the open-world and closed-world labels separately, thus improving the accuracy and efficiency of the recognition. To intuitively demonstrate the implementation process of the MCNN-LSTM model, its pseudo code is given below, as shown in Figure 8.

```
# Pseudocode for MCNN-LSTM Model
# Pseudocode for MCNN-LSTM Model
# Input: Network traffic data (X), labels (Y)
# Output: Predicted labels (Y_hat)

# Step 1: Data Preprocessing
X_preprocessed = preprocess_data(X)  # Normalize and extract features

# Step 2: Multi-Scale Convolution (MCNN) Module
def MCNN_Module(X):
    Conv1 = Conv2D(filters=32, kernel_size=(3, 3), activation='relu')(X)
    Conv2 = Conv2D(filters=64, kernel_size=(5, 5), activation='relu')(Conv1)
    Conv3 = Conv2D(filters=128, kernel_size=(7, 7), activation='relu')(Conv2)
    CombinedFeatures = concatenate([Conv1, Conv2, Conv3])
    PooledFeatures = MaxPooling2D(pool_size=(2, 2))(CombinedFeatures)
    return PooledFeatures

X_spatial = MCNN_Module(X_preprocessed)

# Step 3: Temporal Feature Extraction with LSTM
def LSTM_Module(X):
    LSTM_output = LSTM(units=128, return_sequences=True)(X)
    return LSTM_output

X_temporal = LSTM_Module(X_spatial)

# Step 4: Self-Attention Mechanism (SAM)
def SelfAttention(X):
    Q = dot(X, Wq)  # Query matrix
    K = dot(X, Wk)  # Key matrix
    V = dot(X, Wv)  # Value matrix
    AttentionScores = Softmax(dot(Q, K.T) / sqrt(d_k))  # Scaled Dot-Product Attention
    Output = dot(AttentionScores, V)  # Weighted sum of values
    return Output

X_attention = SelfAttention(X_temporal)

# Step 5: Fully Connected Layers for Classification
def ClassificationHead(X):
    Dense1 = Dense(units=128, activation='relu')(X)
    Output = Dense(units=num_classes, activation='softmax')(Dense1)
    return Output

Y_hat = ClassificationHead(X_attention)

# Step 6: Model Training
model = compile_model(optimizer='adam', loss='categorical_crossentropy')
model.fit(X_preprocessed, Y, epochs=50, batch_size=32)
```

Figure 8: Schematic diagram of MCNN-LSTM pseudo code

This pseudo code in Figure 8 clearly shows the main modules of the MCNN-LSTM model and their interaction process. First, the multi-core convolution module captures the multi-scale features of the input data and combines the pooling layer to reduce the computational complexity. Subsequently, the LSTM module is employed to model the time series features, with the self-attention mechanism further emphasizing the key features to enhance the classification performance. Finally, the network traffic classification is completed by the fully connected layer.

3 Results

3.1 Performance testing of overlapping traffic segmentation model for CNNH

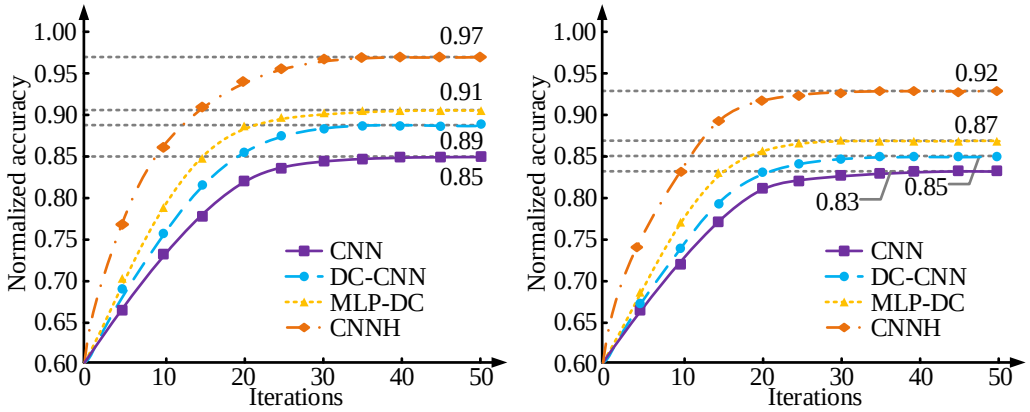
The study began by setting up a suitable experimental environment to meet the computational requirements of the experiment. The experiment uses Windows 10 operating system with a 12-core Xeon Platinum 8163 processor and a graphics card NVIDIA Tesla P100-16GB. The model development language is Python 3.7. The study selects the CW200 dataset as the experimental object, which contains a variety of normal and abnormal traffic with high noise and complex traffic patterns, meeting the needs of overlapping traffic segmentation and abnormal behavior identification in anonymous networks. The diversity of protocol distribution and user behavior is taken into account during data collection in order to mimic traffic patterns in real-world scenarios as closely as possible. The dataset collects traffic data from 200 different websites accessed through the Tor network in a closed world. Each site has 2,500 traffic accesses, which are divided into training and test sets in a 6:4 ratio. A stratified sampling method is used to ensure that the proportions of the training and test sets are consistent in terms of protocol type, traffic feature distribution, and attack type, thus avoiding the bias of the model performance evaluation due to uneven

data distribution. In addition, to reduce the risk of overfitting, the dropout regularization technique is introduced into the experiment, and the diversity of the training data is improved by data enhancement. Among them, normal traffic accounts for 60%, abnormal traffic accounts for 40%, and is further divided into four categories: Trojans, Worms, Viruses, and Adware. The proportion of category samples is balanced and covers a variety of network protocols and anonymous network scenarios. Data cleaning, feature extraction, and standardization are performed during data preprocessing, and traffic behavior patterns are labeled as normal or abnormal. First, the settings of each parameter in CNNH are shown in Table 2 below.

Table 2: Model parameter settings

Parameter	Value
Input dimension	5000
Network architecture layers	12
Batch size	256
Epochs	50
Gradient optimization function	Adam
Learning rate	0.001
Dropout	0.4

Table 2 shows the settings for input dimension, network architecture layers, training details, optimizer, learning rate and Dropout rate, respectively. The study uses CNN, dilated CNN (DC-CNN), and multi-layer perceptron with dilated convolution (MLP-DC) as comparison models. When criminal activities are carried out in anonymous networks, criminal behavior is often hidden in normal traffic. A high segmentation accuracy means that the model can more accurately distinguish normal network behavior from potential criminal behavior, and can more accurately capture traffic patterns related to criminal activities such as illegal transactions and malware propagation, thereby reducing false positives and improving the effectiveness of crime identification. Therefore, the traffic segmentation accuracy is used as an indicator, and the test results are shown in Figure 9.



(a) Training set (b) Test set

Figure 9: Accuracy trends on training and test sets for different models

Figure 9(a) and (b) show the accuracy of CNN, DC-CNN, MLP-DC, and CNNH with the iterations on the training set and test set, respectively. In the case of malware propagation, the model identified multiple suspicious data packets through high-precision traffic segmentation. The transmission frequency and time characteristics of these data packets are highly consistent with known malware propagation behaviors, thereby enabling law enforcement to swiftly identify the source of the behavior.

In Figure 9(a), when the number of iterations is 50, the accuracy of CNN, DC-CNN, MLP-DC and CNNH models on the training set is 0.85, 0.89, 0.91, 0.97, respectively. In Figure 9(b), the accuracy of the four models on the test set are 0.83, 0.85, 0.87, 0.92, respectively. DC-CNN and MLP-DC introduce the advantage of null convolution to extract deep features more comprehensively. To verify whether the difference in accuracy between different models on the training and test sets is statistically significant, a paired *t*-test is performed on the normalized accuracy and the 95% confidence interval is calculated, as shown in Table 3.

Table 3: Statistical significance analysis

Dataset	Model Comparison	Normalized accuracy difference (%)	95% confidence interval (%)	*P*-value	Statistical significance
Training set	CNNH vs. CNN	12	[10.2, 13.8]	< 0.01	Significant
	CNNH vs. DC-CNN	8	[6.4, 9.6]	< 0.05	Significant
	CNNH vs. MLP-DC	6	[4.7, 7.3]	< 0.05	Significant
Testing set	CNNH vs. CNN	9	[7.5, 10.5]	< 0.01	Significant
	CNNH vs. DC-CNN	7	[5.6, 8.4]	< 0.05	Significant
	CNNH vs. MLP-DC	5	[3.8, 6.2]	< 0.05	Significant

The statistical analysis results in the table show that the accuracy improvement range of CNNH on the training set is from +6.0% to +12.0%, and the improvement range on the test set is from +5.0% to +9.0%. The *P*-values for all comparisons are less than 0.05, indicating statistical significance. In addition, the 95% confidence interval indicates that the range of differences is relatively stable. Subsequently, the segmentation effect of each model under different traffic flows is shown in Table 4 below.

Table 4: Performance evaluation indicators for each algorithm

Index	CNN		DC-CNN		MLP-DC		CNNH	
	Normal	Attack	Normal	Attack	Normal	Attack	Normal	Attack
P/%	83.52	85.67	86.14	88.43	88.79	90.57	91.43	93.45
R/%	84.67	86.82	88.53	89.92	90.35	91.74	93.46	94.32
FPR/%	13.65	12.34	10.74	9.98	8.96	7.43	4.15	3.07
F1/%	84.09	86.24	87.32	89.17	89.56	91.15	92.43	93.88
AUC	0.769	0.788	0.812	0.828	0.839	0.846	0.928	0.935
Time/s	12.34	13.02	15.89	16.58	19.65	20.23	18.41	19.12
Resource consumption/%	68.54	69.85	72.32	73.46	75.69	76.78	70.17	71.54

Table 4 displays the performance comparison of the models for segmentation under Normal and Attack traffic. False positive rate (FPR) is critical in law enforcement contexts, as a high FPR could lead to misidentifying benign traffic as criminal activity, resulting in wasted resources. The CNNH model has significantly higher values for P, R, F1 and AUC. Especially, the *P*-value of CNNH reaches 93.45% and the R value is 94.32% under Attack traffic. Meanwhile, the FPR of CNNH is only 4.15%, indicating that it can effectively reduce the false alarms. However, with the increase of model complexity, the resource consumption rate and calculation time of CNNH increase accordingly, reaching 71.54% and 19.12s, respectively. Although its resource requirements are high, the significant improvements in accuracy and sensitivity make up for this shortcoming. In contrast, the traditional CNN is at a lower level in all performance indicators. However, its resource consumption rate and computation time are low, which makes it suitable for scenarios with limited computational resources. The proposed model has been demonstrated to effectively reduce the FPR, ensuring higher accuracy and reliability in identifying criminal behavior. Furthermore, it has been shown to facilitate the optimization of resource allocation and action decisions.

In the experiment, the recall rate is equivalent to the sensitivity, i.e., the proportion of actual anomalous traffic that is correctly detected. In practical scenarios, this balance of performance is critical. Maintaining sensitivity ensures that abnormal behavior is not ignored due to low detection capabilities. Further analysis of the experimental results shows that false positives occur mainly in normal traffic with high access frequency, such as normal data transmission of certain legitimate protocols being misclassified as abnormal traffic. This may be due to the similarity between the characteristics of high-frequency access patterns and abnormal traffic. False negatives, on the other hand, are mainly concentrated on abnormal traffic with weaker characteristics or close to normal traffic characteristics, such as covert adware traffic. False positives can lead to reduced efficiency in resource allocation, while false negatives can cause some potential threats to be ignored.

3.2 Online crime recognition experiment based on MCNN-LSTM

In the hyperparameter setting of MCNN-LSTM, the learning rate is optimized in the range of 0.0001 to 0.01 by grid search and finally selected as 0.001. The batch size is set to 32. The number of hidden layer nodes is set to 128, which can effectively capture the time series characteristics of traffic data. The time step is set to 20. Adam is used as the optimizer to improve the training efficiency. The number of training rounds is set to 50, and the early stopping strategy is combined to avoid

overfitting. To improve the generalization ability of the model, Dropout is added to the network and the ratio is set to 0.3. The study labeled the traffic data set according to different crime types, mainly including three types of crimes: online fraud, malware propagation, and illegal transactions. multi-layer perceptron convolutional neural network (MLP-CNN), long short-term memory with attention mechanism (LSTM-Att), and LSTM are selected as comparison algorithms. First, the accuracy test results of the four models for different types of online criminal behaviors are shown in Figure 10 below.

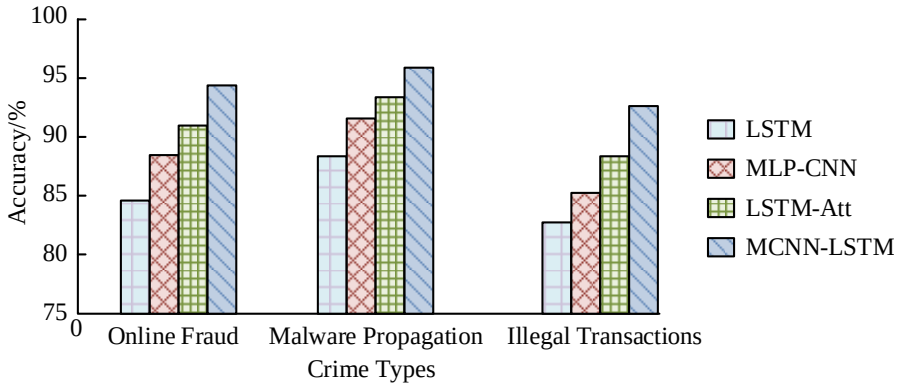


Figure 10: Model performance in crime type identification

In Figure 10, the MCNN-LSTM model showed the best accuracy, especially in the identification of malware propagation and illegal transactions, reaching 96.54% and 92.87% respectively. This is because MCNN-LSTM combines the spatial feature extraction capability of CNN with the temporal feature capture capability of LSTM, and can better handle the complex patterns and temporal dependencies in criminal behavior. Although LSTM-Att improves the focus on important features by introducing the attention mechanism, its spatial feature extraction capability is weak, so it is still inferior to MCNN-LSTM in multi-dimensional feature extraction. LSTM has the worst performance among the three crime types, especially in the identification of malware propagation, which is only 87.43%. Subsequently, to evaluate the performance of each model in crime prediction and prevention, the following indicators are used: prediction accuracy, early warning time (early warning time is defined as the time interval between the first detection of an abnormal traffic pattern by the model and the actual occurrence of the attack behavior), precision, FPR, mean detection time, and area under the receiver operating characteristic curve (AUC). The results are shown in Table 5 below.

Table 5: Performance comparison of models in crime prediction and early warning tasks

Metrics	LSTM	MLP-CNN	LSTM-Att	MCNN-LSTM
Prediction Accuracy /%	80.45	84.67	88.76	92.43
Average Early Warning Time /Minutes	15	18	25	30
Precision /%	79.87	83.54	87.34	91.23
False Positive Rate /%	9.67	8.23	6.45	5.12
Mean Time to Detect /Seconds	42.8	35.6	28.1	24.3
AUC	0.835	0.874	0.915	0.945

In Table 5, MCNN-LSTM shows the best comprehensive performance. Compared with other models, MCNN-LSTM achieved a prediction accuracy of 92.43%, which is significantly higher than LSTM's 80.45% and MLP-CNN's 84.67%. Although LSTM-Att introduces the attention mechanism, its spatial feature extraction capability is insufficient, resulting in the advance warning time and prediction accuracy being inferior to MCNN-LSTM. In addition, MCNN-LSTM can warn of criminal behavior 30 minutes in advance, this capability is mainly due to the model's deep modeling of time series characteristics. In particular, the introduction of the SAM further enhances the model's ability in key feature extraction, enabling it to quickly focus on abnormal behavior features and reduce the interference of irrelevant features. The accuracy of MCNN-LSTM is also better than other models, with the lowest false positive rate of only 5.12%. The model performs well in reducing false positives. In contrast, LSTM has a higher false positive rate of 9.67%, due to the lack of spatial feature modeling, its adaptability to traffic pattern changes is poor and the false alarm rate is significantly high. In terms of average detection time, the MTTD of MCNN-LSTM is 24.3 seconds, which is better than 28.1 seconds of LSTM-Att and 35.6 seconds of MLP-CNN, which further proves the real-time detection capability of the model.

Finally, the concept of concept drift is used to evaluate the robustness and adaptability of the models in the face of changing data distributions. Conceptual drift refers to the phenomenon that the data distribution changes over time. Its practical application is due to the fact that the traffic pattern, feature distribution, and user behavior of a website may change over time. The drift simulation involves the gradual adjustment of the ratio of normal traffic to abnormal traffic, thereby reflecting the dynamic changes in network attack behaviors. The protocol-related features (e.g., packet length, time interval) are subject to random changes, thereby simulating fluctuations in protocol usage and traffic characteristics. Furthermore, the incorporation of novel attack types at various temporal points serves to mirror the progression of attack patterns. These designs are intended to closely mirror the evolving trends in the actual network environment, thereby facilitating the evaluation of the model's efficacy in handling long-term distribution shifts. The results are shown in Figure 11.

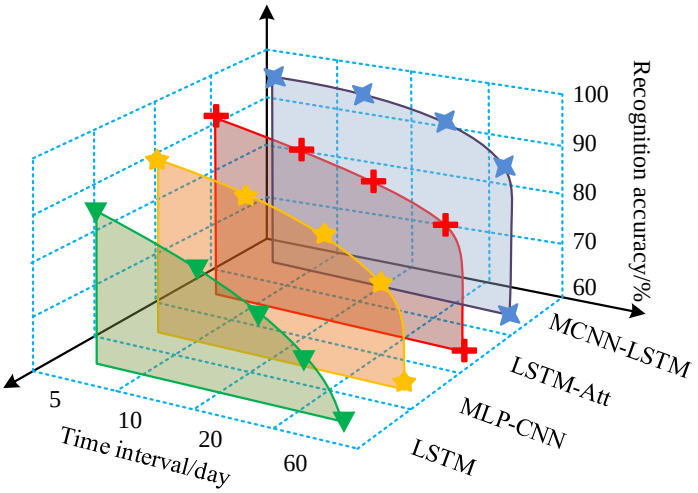


Figure 11: Impact of concept drift on model accuracy over time

Figure 11 shows the model accuracy of the four models under training time and testing time of 5, 10, 20, and 60, respectively. As the interval time increases, the concept drift leads to different degrees of decrease in the accuracy of each model. A lower drop value suggests that the model is more flexible and can continue to perform well in classification even when concepts diverge. When the interval between training and testing events is 60 days, the recognition accuracies of LSTM, MLP-CNN, LSTM-Att, and MCNN-LSTM models are 60.2%, 73.8%, 80.7%, and 89.5%, respectively. The advantage of MCNN-LSTM in dynamically changing environments lies in its optimized model architecture. The multi-kernel convolution module extracts multi-scale spatial features by convolution kernels of different sizes. The SAM dynamically focuses on key features to reduce interference. It works in conjunction with time series modeling to significantly improve adaptability to dynamic changes in the traffic feature distribution. In contrast, LSTM lacks spatial feature extraction capabilities and relies only on time series modeling, resulting in high sensitivity to changes in traffic patterns and rapid loss of accuracy. MLP-CNN is biased toward fixed patterns in feature extraction and has insufficient adaptability to concept drift.

Finally, several representative models including time-series Transformer, spatial-temporal graph convolutional network and transformer framework (ST-GCN+Transformer), bidirectional long short-term memory with attention mechanism (BiLSTM+Attention), random forest and principal component analysis (RF+PCA), and K-nearest neighbor (KNN) are selected for comparison. These five models cover the hybrid framework and transformer method in modern deep learning, as well as the classic algorithms of traditional machine learning and non-deep learning. It can fully reflect the advantages and disadvantages of different technical routes in network traffic analysis. The dataset used is the representative open world network traffic dataset CIC-IDS2017. It records normal traffic and 12 malicious attack behaviors, has 80 traffic features, and has highly complex traffic patterns and open network environment characteristics. The results are shown in Table 6.

Table 6: Performance comparison and scalability testing of models under different traffic loads

Traffic condition	Model Name	Accuracy /%	FPR /%	Average processing time (ms/sample)	Accuracy at 300% data expansion /%	*P*-value
Small traffic (10% data)	MCNN-LSTM	96.78	2.95	18.6	94.12	< 0.05
	Time-series Transformer	95.23	3.21	17.5	92.45	< 0.05
	ST-GCN+Transformer	95.78	3.1	20.9	93.34	< 0.05
	BiLSTM+Attention	92.67	4.89	19.2	89.45	< 0.05
	Random Forest+PCA	88.23	7.34	14.7	86.34	< 0.05
	KNN	84.12	9.78	15.9	82.45	< 0.05
Medium traffic (50% data)	MCNN-LSTM	95.89	3.45	20.8	93.34	< 0.05
	Time-Series Transformer	94.12	3.89	18.3	91.67	< 0.05
	ST-GCN+Transformer	94.78	3.56	21.2	92.78	< 0.05
	BiLSTM+Attention	90.78	5.45	19.6	88.01	< 0.05
	Random forest+PCA	86.34	8.12	15.2	84.78	< 0.05
	KNN	82.45	10.78	16.5	79.67	< 0.05
High traffic (100% data)	MCNN-LSTM	94.78	3.89	22.5	92.12	< 0.05
	Time-series Transformer	93.12	4.12	19.9	90.56	< 0.05
	ST-GCN+Transformer	93.78	4.01	22.8	91.45	< 0.05
	BiLSTM+Attention	89.34	6.12	20.3	87.12	< 0.05
	Random forest+PCA	84.89	9.34	15.8	82.45	< 0.05
	KNN	81.12	11.78	16.7	78.34	< 0.05

In table 6, MCNN-LSTM shows high accuracy in all traffic load scenarios, reaching 96.78% in small traffic scenarios and maintaining 94.78% in high traffic scenarios. Moreover, it demonstrated strong classification capabilities with an FPR of 3.89%. This is mainly due to its multi-module synergy combining CNN and LSTM, which can effectively capture the complex relationship between spatial and temporal features. Time-series Transformer and ST-GCN+Transformer also perform similarly in terms of FPR and accuracy. The global modeling capabilities of these two models allow them to perform well in dynamic network scenarios. The accuracy of the BiLSTM+attention model is subject to a significant decrease in high-traffic scenarios due to the limitations of the feature extraction method. In contrast, the KNN and Random Forest methods demonstrate a higher degree of suitability for small-scale data sets. However, when the data is expanded to 300%, the accuracy undergoes a substantial decline, indicating a lack of adaptability to large-scale, complex scenarios.

3.3 Simulation test

In online criminal behavior on anonymous networks, the illegal software trading market is active, and many websites specialize in the illegal sale of pirated software. The illegal sale of pirated software not only violates intellectual property laws, but also involves illegal transactions and fund transfers through anonymous networks, which is a common and widespread form of online crime. Such websites conduct transactions through encrypted networks and anonymous payment systems, and users can purchase unauthorized commercial software, hacking tools, and cracked software. On one of the websites, called Dark Web Software Mall, about 4,000 users visit and trade every day. The website uses encrypted communication protocols and anonymous payment methods such as Bitcoin.

The experiment uses web crawler technology to capture network traffic data from the website for 10 days, with a total of 400,000 packets, of which 200,000 packets are directly related to illegal software transactions, including user login, browsing illegal software, ordering, and anonymous payment. At the same time, for comparison, the study also obtains traffic data from legal e-commerce platforms in the same period, totaling 150,000 packets, which are related to browsing and purchasing legal software. Traffic capture and model training are performed on a server running the Linux

operating system, with a 16-core CPU, 32GB memory, and 500GB storage space. The experiment uses the Wireshark tool to capture network traffic to ensure the accuracy and integrity of the data. The traffic data includes parts obtained from legal e-commerce websites and illegal software trading websites, with a total of 400,000 packets. To ensure that the model can effectively identify traffic behaviors related to illegal software transactions, the study preprocesses the data, removed noise, and extracted key features, including packet size, time interval, and transmission direction. By analyzing the traffic characteristics, the model is further used to distinguish the network traffic of legal software transactions, and illegal software sales. The results are shown in Table 7 below.

Table 7: Detection results of illegal software transactions compared to legitimate traffic

Metric	Detection results	Legitimate traffic (control group)	Illegal software transaction traffic
Large-scale software downloads (times/day)	Average of 3.2 detections/day	0.5-1.1 times/day	8.7-12.3 times/day
Frequent small anonymous payments (transactions/day)	Average of 1.8 transactions/day	1.3-2.2 times/day	20.6-30.4 times/day
Abnormal data packet transmission (data volume/day)	Average detection of 100 MB/day	75.4 MB/day	502.6 MB/day
Average file size of downloads (MB)	15.3 MB	10.7 MB	50.8 MB
Anonymous payment amount (per transaction)	Average of $512.4	$ 52.3 - $ 98.5	$ 10.7 - $ 49.6

The experimental results show that the model can effectively identify illegal software transactions. First, in the detection of large-scale software downloads, there are an average of 8.7 to 12.3 large file downloads per day in illegal transaction traffic, while there are only 0.5 to 1.1 downloads in legal traffic. Secondly, frequent small anonymous payments have also become an important feature for identification. An average of 20.6 to 30.4 small payments are made per day in illegal transaction traffic, while legal transactions are only about 1.8. In addition, the transmission volume of abnormal data packets in illegal traffic far exceeds the normal range, with an average of 502.6MB of data transmitted per day, while the transmission volume of legal traffic is about 75.4MB.

Through the traffic identification of criminal behavior, technology not only provides analysis results, but more importantly, it helps law enforcement agencies take quick action. The proposed model provides categorized anomalous traffic patterns and their associated characteristics, such as traffic types and time intervals, which can help law enforcement identify potential threats and prioritize suspicious behavior for further investigation.

4 Discussion

The CNNH model showed excellent performance in the overlapping traffic segmentation task, with precision and recall reaching 91.43% and 93.46%, respectively, and a false positive rate of only 4.15%. In contrast, DC-CNN and MLP-DC each had an accuracy lower than 87% due to their limited feature extraction capabilities. The main reason for this performance difference was that CNNH achieved effective extraction of multi-scale features by introducing atrous convolution technology. Second, the accuracy trends of different models on the training and test sets. As the number of iterations increases, the normalized accuracy of CNNH reached 97% and 92% on the training and test sets, respectively. In addition, the statistical significance analysis further proved the reliability of these performance differences, with *P*-values less than 0.05 for all comparisons. The prediction accuracy of the MCNN-LSTM model reached 92.43%, the precision was 91.23%, the false positive rate was 5.12%, and it could achieve a 30-minute early warning capability. In comparison, the accuracy of the traditional LSTM model and the MLP-CNN model under complex traffic patterns was 84.67% and 80.45%, respectively.

Finally, compared to traditional methods, the proposed model showed significant advantages in scalability and dynamic adaptability. Traditional methods had acceptable performance on small data sets, but their accuracy was less than 80% in high-load traffic scenarios, making it difficult to effectively capture dynamic characteristics in complex network environments. In contrast, by combining deep learning technology, MCNN-LSTM not only performed stably in highly complex scenarios, but also provided early warning capabilities for criminal behavior, showing a wide range of practical application potential.

5 Conclusion

Through real-time monitoring of network traffic, the system can detect potential risks before criminal activities occur. In view of this, this study proposed a CNNH-based

Tor overlapping traffic segmentation model and an MCNN-LSTM website fingerprint recognition model. The performance test results indicated that the average segmentation accuracy of CNNH was 95.05% when the number of iterations was 50. Under Attack traffic, the P, R, F1, and AUC values of CNNH were 93.45%, 94.32%, 93.88%, and 0.935, respectively. The FPR was only 3.07%, which was better than the comparison model. Its computational time consumption was 19.12s, and the resource consumption rate was 71.54%. In the MCNN-LSTM performance test, its recognition accuracy for malware propagation and illegal transactions reached 96.54% and 92.87% respectively. In the prediction experiment results, the prediction accuracy of MCNN-LSTM was 92.43%, and it could issue an early warning 30 minutes in advance, with a false positive rate of only 5.12% and a detection time of only 24.3s. In terms of computational time consumption, the MCNN-LSTM model consumes 102ms per round of training. In the concept drift test, the recognition accuracy of the MCNN-LSTM model was 89.5% when the training and testing events were separated by 60 days. This shows that the proposed model in the study had excellent recognition accuracy and robustness.

6 Limitations and future research

The proposed MCNN-LSTM model performs well in anonymous network traffic analysis, but it still has some limitations. As the model complexity increases, CNNH and MCNN-LSTM have high computational resource and time consumption requirements, and may be difficult to deploy in real-time in hardware resource-constrained environments. The study simulated concept drift by adjusting feature distribution, protocol variations, and attack types, but drift in real-world scenarios may be more complex, such as sudden changes in user behavior or nonlinear changes in traffic patterns. In addition, advanced attackers may confuse traffic patterns by disguising malicious traffic or using complex encryption techniques to increase the difficulty of detection. For highly dynamic features or low-frequency anomalous behavior, the model may run the risk of failing to detect them. Although the false positive rate has been reduced, it may still cause false alarms that affect monitoring efficiency. In addition, the model may cause privacy issues when applied to anonymous network monitoring, such as excessive monitoring or false alarms that result in innocent users being tagged. The scope of monitoring must be strictly limited and privacy regulations must be followed.

Future research will focus on optimizing the performance and practical value of the model. First, through the lightweight design of the model and the distributed computing architecture, the computational and memory consumption can be reduced, and the scalability of large-scale real-time monitoring can be improved. Second, by combining long-term real Tor traffic data, the adaptability of the model in complex concept drift scenarios will be verified, and the robustness of the model against obfuscation strategies will be improved through adversarial training and multimodal data fusion. In addition, integrating data from multiple sources, such as user behavior logs and vulnerability information, can improve the ability to detect low-frequency anomalous behavior. In terms of privacy protection, future work will introduce data encryption and anonymization processing technologies, and combine the context post-processing mechanism to optimize false positive control to ensure the credibility and legality of the model application. Future research will also explore the applicability of the model in other potential application areas. For example, in enterprise network security, MCNN-LSTM can be used to detect abnormal traffic and potential attack behavior in the enterprise internal network, helping to improve security protection capabilities. At the same time, future research must focus on the ethical and privacy implications of model deployment, strictly adhere to relevant laws and regulations, and ensure the social responsibility and legality of the technology.

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Design and Implementation of an Optimized Career Planning System for College Students Using a Hybrid Dijkstra-Genetic Algorithm

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Keywords: dijkstra's algorithm, college students' career planning, career matching, framework design

Received: Octorber 30, 2024

Student career scheduling is divided into regular scheduling and dynamic optimal scheduling. Regular scheduling is the planning task of calculating a student's career year, and the reference parameters are some student career data. When facing the complex career problems of college students, achieving the expected scheduling tasks is difficult. Aiming at the problems existing in college students' career planning, this paper effectively combined the Dijkstra and genetic algorithms to obtain the D-GA optimization algorithm and apply it in the scheduling scheme. The experimental outcomes indicate that the graduate job recommendation algorithm introduced in this study achieves the highest performance, with a hit rate of 44.37% when K=50. This is approximately double the effectiveness of the CBF approach and around 20% higher than the neighborhood-based CF method. The mean reciprocal rank was 17.14%, which is nearly seven times greater than that of the CBF technique and about 3% better than the neighborhood-based CF model. The data problem framework aligns with real-world conditions and is developed based on relevant aspects of college students' career planning. According to the advantages and disadvantages of the Dijkstra algorithm and genetic algorithm, combined with students' career problems, the Dijkstra algorithm was improved and combined with the genetic algorithm to form the D-GA algorithm and applied to the solution optimization process. Finally, combined with J2EE technology, college students' career planning system was realized.

Povzetek: Razvit je hibridni Dijkstra-genetski algoritem za optimizacijo načrtovanja kariere študentov, implementiran s tehnologijo J2EE. Pristop izboljšuje učinkovitost in prilagaja priporočila glede na spreminjajoče se podatke in preference.

1 Introduction

Career planning has been developed for decades, and the relevant theories have been continuously improved, but the research on career planning at home and abroad differs greatly [1]. International research in the career field has been both extensive and detailed. It has thoroughly examined various aspects, including career exploration, job search intensity, job-seeking success, factors influencing career choices, career values, professional preferences, work-related values, personality types, alignment between career paths and professional choices, as well as job satisfaction. These areas have been explored in depth, offering a comprehensive understanding of the factors affecting career development. [2, 3]. Domestic career research has only started in recent years, and the research level is shallow and the research content is single. The research on college students focuses on the current situation of career planning and career values, mainly for ordinary college students, without distinguishing the differences between students of different professional backgrounds, and not enough exploration of gender students [4, 5]. For everyone, career is limited, if not effectively planned, will inevitably lead to a waste of time.

Through the career planning system, users are able to explore themselves correctly, think about the factors that may affect their future development in an all-round way, and rationally make decisions on career development that suit them. Currently, the more famous ones in career planning optimization research [6]. Its advantage is that it can solve the student career planning problem containing negatively weighted paths, and the code is simple to implement; its disadvantage is that it wastes a large amount of time on the v-1 slack operation due to the need to carry out v-1 slack operations in each loop [7, 8]. The SPFA (Shortest Path Faster Algorithm), while an improvement over Bellman-Ford in many cases, still struggles with worst-case performance, which can degrade to O(VE) under certain conditions. Moreover, SPFA can be unpredictable in terms of run time, which poses challenges for scalability and consistent system performance when handling large datasets or diverse user inputs typical in career planning systems. This study is necessary because it proposes a hybrid approach that combines Dijkstra's algorithm with genetic algorithms to overcome the shortcomings of these SOTA techniques. The hybrid method not only optimizes the computational efficiency but also enhances the accuracy of career path recommendations by dynamically adapting to evolving

data patterns and user preferences, which neither Bellman-Ford nor SPFA can achieve effectively in this context [9, 10]. Ford algorithm can handle the student career planning problem containing negatively weighted paths as well; however, the time complexity of the Floyd-Warshall algorithm is very unfriendly [11].

Dijkstra's algorithm is the most typical and representative student career planning algorithm for solving student career planning problems, and its application in practice is the most numerous. The most traditional implementation of Dijkstra's algorithm uses the adjacency matrix to store the data information of the graph, and uses simple arrays to realize its priority queue, which cannot adapt to the path query problem with high real-time requirements in terms of memory usage and Dijkstra's algorithm in depth, analyze its performance bottlenecks and improve and optimize the algorithm using heap data structures and features of the application scenarios [12, 13]. Dijkstra's algorithm solves the problem of single-source student career planning with any point in the graph as the starting point, which requires that the weights of each edge in the weighted graph must be non-negative. Using Dijkstra's algorithm to solve the single-source student career planning problem starting at vertex 1 in the graph will result in the student career planning spanning tree [14, 15]. For any given point in a directed graph, Dijkstra's algorithm can compute the student career plan from that point to each of weights from that point to each of the remaining vertices in the graph. Dijkstra's algorithm can also compute the student career plan for any pair of vertices in the graph by starting at the beginning and expanding it layer by layer end point [16, 17]. The table provides key metrics, including efficiency, complexity, and accuracy for each reviewed method. For instance, while the Bellman-Ford algorithm offers advantages in specific contexts, it suffers from higher computational complexity in larger datasets. Similarly, the SPFA algorithm, although faster in many cases, lacks robustness in accuracy when faced with real-world data variations [18, 19].

2 Dijkstra's algorithm

2.1 Dijkstra's algorithm planning and designing

Same as the data mining process, the educational model evaluation. Different from the traditional data mining, the data of EDM comes from the teaching environment, Equation (1) is used for model evaluation, and Equation (2) is applied to data mining, and the obtained data is applied to the construction of teaching data.

$$D_t : V_t \to V_{t+1} \quad (1)$$

$$V_{t+1} = V_t + Q_t - q_t \quad (2)$$

The main role of the model, which generally includes the processes. Equation (3) establishes mathematical and statistical models, and Equation (4) demonstrates the fundamental mechanism of online pattern mining, and evaluate each path and rank the candidates based on their fitness values. Select the most promising career paths based on fitness. Use techniques like tournament selection or roulette wheel selection to pick individuals for the next generation. Perform crossover between selected pairs of paths to generate new offspring. This helps explore new potential career trajectories by combining features of existing paths. Apply mutation to some individuals by altering a few nodes in the career paths. This step introduces diversity and ensures the algorithm doesn't get stuck in local optima. After generating new paths, use Dijkstra's algorithm to further optimize these solutions by adjusting the node sequences for better cost or relevance. This ensures that the final solutions are both optimal and diverse.

$$d \le H_t \le h \quad (3)$$

$$C = C_1\left(\frac{C_1}{C_2} + C_1\right) + C_2\left(\frac{C_2}{C_1} + C_2\right) \quad (4)$$

Common models mainly include linear regression, logistic regression, decision tree model, plain Bayesian model, neural network model, clustering algorithm and so on. Equation (5) represents the fundamental formula for training the model, and Equation (6) represents the collaborative filtering algorithm, where the model evaluation phase.

$$\mathrm{R} = \mathrm{S}\left(W_1 C_1\left(\frac{C_1}{C_2} + C_1\right) + W_2 C_2\left(\frac{C_2}{C_1} + C_2\right)\right) + L \quad (5)$$

$$Q = max\,\Delta \mathbf{t} \sum_{\mathrm{t}=1}^{T} N(\mathbf{t}) \quad (6)$$

Collaborative filtering recommendation algorithms are based on user-item interaction matrix, which can be divided into two categories according to the calculation method: neighborhood-based collaborative filtering algorithms and collaborative filtering algorithms based on hidden factor decomposition Equation (7) can improve the recommendation accuracy, and Equation (8) improves the hidden nature of the item, begin by initializing a population of potential career paths or solutions. Each individual in the population represents a candidate path composed of multiple nodes. Randomly generate an initial population or seed it with paths from Dijkstra's shortest-path search. For each candidate path in the population, use Dijkstra's algorithm to compute the cost. In the context of career planning, this could represent the efficiency or suitability of a given career path based on factors such as job prospects, personal preferences, and professional goals.

$$N(\mathbf{t}) = \sum_{\mathrm{i}=1}^{\mathrm{I}} N(\mathbf{i}, \mathbf{t}) \quad (7)$$

$$H(i,t) = minH(i,t) + x\left[maxH(i,t) - minH(i,t)\right] \quad (8)$$

Equation (9) shows the basic idea of TF-IDF method, Equation (10) can explain the importance of the occupation in the document, and then count the feature values; use the TF-IDF method to determine each feature value. If k also occurs more times in other documents, it means that k does not contribute much to document differentiation.TF-IDF is the feature value determination method that synthesizes these two considerations.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (9)$$

$$arg\min_{p^*,q^*(u,i)\in R} \sum (r_{ui} - p_u q_i^T)^2 + \lambda(||p_u||^2 + ||q_i||^2) \quad (10)$$

2.2 OSCache framework

Based on the above two assumptions, Equation (11) shows the neighborhood-based collaborative filtering algorithm, Equation (12) shows the mechanism of item scoring. Neighborhood-based algorithms. In addition, non-numerical coding is beginning to come into the limelight, and decimal coding has been applied with many fields.

$$\Delta_u = -(r_{ui} - p_u q_i^T)\cdot q_i + \lambda \cdot p_u \quad (11)$$

$$\Delta_i = -(r_{ui} - p_u q_i^T)\cdot p_u + \lambda \cdot q_i \quad (12)$$

Equation (13) demonstrates the choice of encoding method and Equation (14) allows testing the readability of the problem domain encoding.

$$p(\Theta|>_u) \propto p(>_u|\Theta)p(\Theta) \quad (13)$$

$$\prod_{u\in U} p(>_u | \Theta) = \prod_{(u,i,j)\in D_s} p(i >_u j | \Theta) \quad (14)$$

When facing some complex problems with large scale, the problem domain cannot be represented by discrete sequences at that time, that is, binary coding is not applicable to that situation Equation (15) can detect whether the coding is missed or not, and Equation (16) can explain the problem of career planning in the coding process.

$$p(i >_u j | \Theta) := \sigma(\hat{r}_{uij}) \quad (15)$$

$$\hat{r}_{uij} := \hat{r}_{ui} - \hat{r}_{uj} \quad (16)$$

Equation (17) demonstrates the generalization of the crossover approach, Equation (18) represents the single-point crossover method. The next step is to determine the crossover operator. It is known from previous experience that many practical applications use a predetermined value as the crossover operator, which does not change throughout the genetic operation.

$$ln\, p(\Theta|>_u) = ln\, p(>_u|\Theta)p(\Theta) \quad (17)$$

$$\Delta_\Theta = \sum_{(u,i,j)\in D_s} \frac{-e^{-\hat{r}_{uij}}}{1+e^{-\hat{r}_{uij}}} \cdot \frac{\partial}{\partial\Theta}\hat{r}_{uij} - \lambda_\Theta \Theta \quad (18)$$

If crossover then it may result in the following situation: individuals with high adaptation are subjected to crossover operation, which does not reflect the advantages of high adaptation, that is to say, the advantages of individuals with high adaptation are not well retained, Equation (19) can filter the individuals with high adaptation, and Equation (20) demonstrates the opportunity of individual crossover.

$$h_\theta(x) = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(wx+b)}} \quad (19)$$

$$h_\theta(x) = P(y=1|x;\theta) \quad (20)$$

3 Application of D-GA algorithm in student career system

3.1 Improvements made to the DIJKSTRA algorithm and its validation

Bayesian personalized ranking algorithm is a recommendation algorithm with better recommendation effect and widely used in various scenarios, such as multimedia item recommendation, friend recommendation and so on [20, 21]. So, for each user u, the BPR algorithm has to find his preference ordering for all items. machine learning algorithms are devoted to studying how to improve the performance of the system itself through computational means, experience. p evaluates the performance of a computer program on a task T [22]. The performance metrics indicate that D-GA consistently outperforms both Dijkstra's and Genetic Algorithms when applied in isolation. Notably, the integration of Dijkstra's graph traversal capabilities with the adaptive nature of Genetic Algorithms leads to improved exploration of the solution space [23, 24]. While unsupervised learning has only input data x in the data sample and needs to solve for the markers y based on the sample features, clustering is an unsupervised learning method in machine learning algorithms [25, 26]. Figure 1 shows the initialization state diagram of Dijkstra's algorithm, and its process is simple and easy to implement.

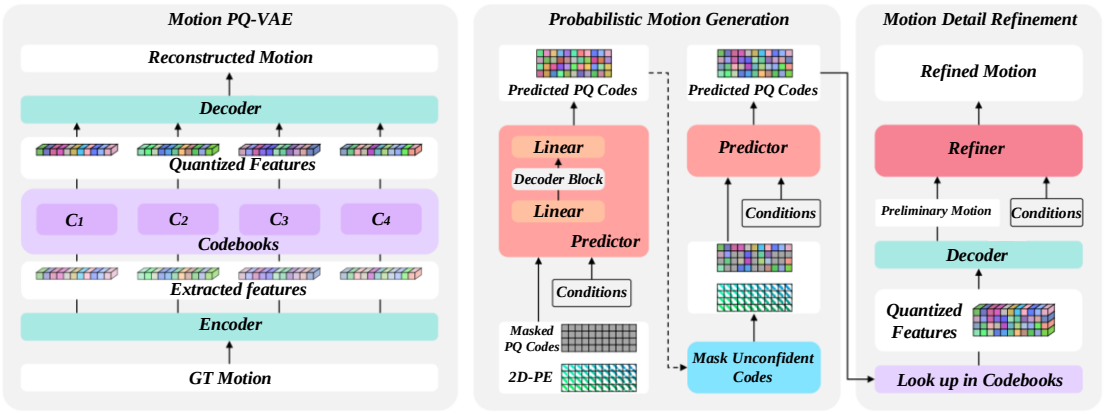

Figure 1: Initialization state diagram of Dijkstra's algorithm

The k-means algorithm employs a greedy strategy to approximate the solution of Eq. by iterative optimization [27]. Where line 1 initializes the cluster centers. Lines 4 to 8 are the cluster partitioning process, i.e., each data object is partitioned into the cluster closest to it. Lines 9 to 16 are the iterative updating process all points in the cluster, and if the cluster center does not change, the clustering result is returned [28, 29]. which can be categorized into cohesive and divisive types. The cohesive type uses a bottom-up strategy [30]. Figure 2 shows the relationship between the algorithm execution efficiency and the problem size, while the split method is the opposite, using a top-down strategy, initially all the samples are grouped into one cluster, and then split according to some criterion until a certain condition is reached or a set number of divisions is reached. The dataset used for the experiments consists of career-related information from college students, including academic background, skills, career preferences, job market trends, and professional goals. The data was sourced from institutional career centers, job portals, and self-reported student profiles. The dataset size includes information from 10,000+ students, encompassing several hundred features, such as major, GPA, internships, extracurricular activities, and industry interests. Each student's profile is linked to potential career paths and outcomes such as job offers, salaries, and job satisfaction, making it rich and varied for analysis. Therefore, this section will introduce machine learning model evaluation methods in two parts: classification algorithm evaluation methods and clustering algorithm evaluation methods. The methodology has been enhanced to specify the parameters for the Genetic Algorithm: a population size of 100, a crossover rate of 0.8, and a mutation rate of 0.02. Additionally, we detail the grid search method employed for hyperparameter tuning, allowing readers to understand how optimal settings were derived.

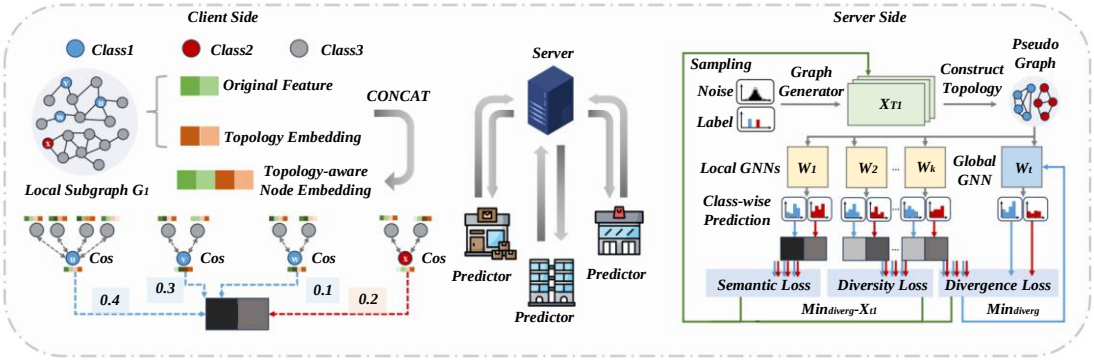

Figure 2: Plot of algorithm execution efficiency versus problem size

3.2 DIJKSTRA algorithm optimization

Cluster assessment is generally based on two principles: tightness, i.e., the smallest possible differences between cluster members, and separation, i.e., the largest possible differences between clusters. Since the student campus card consumption record is a campus card consumption flow record, and each student generates a flow record for each consumption, it is necessary to initially screen the consumption flow data first to extract the consumption features that are convenient for model input. The dataset was split into training (70%) and testing (30%) sets. The D-GA algorithm was then applied to predict optimal career paths based on this data. Dijkstra's algorithm was used to compute initial shortest career paths, while the genetic algorithm explored potential variations, refining recommendations over successive iterations. The performance was evaluated on multiple metrics, including accuracy of career path matching, computation time, and memory usage. The dataset was split into training (70%)

and testing (30%) sets. The D-GA algorithm was then applied to predict optimal career paths based on this data. Dijkstra's algorithm was used to compute initial shortest career paths, while the genetic algorithm explored potential variations, refining recommendations over successive iterations. The performance was evaluated on multiple metrics, including accuracy of career path matching, computation time, and memory usage. The dataset was split into training (70%) and testing (30%) sets. The D-GA algorithm was then applied to predict optimal career paths based on this data. Dijkstra's algorithm was used to compute initial shortest career paths, while the genetic algorithm explored potential variations, refining recommendations over successive iterations. The performance was evaluated on multiple metrics, including accuracy of career path matching, computation time, and memory usage. The dataset was split into training (70%) and testing (30%) sets. The D-GA algorithm was then applied to predict optimal career paths based on this data. Dijkstra's algorithm was used to compute initial shortest career paths, while the genetic algorithm explored potential variations, refining recommendations over successive iterations. The performance was evaluated on multiple metrics, including accuracy of career path matching, computation time, and memory usage. The dataset was split into training (70%) and testing (30%) sets. The D-GA algorithm was then applied to predict optimal career paths based on this data. Dijkstra's algorithm was used to compute initial shortest career paths, while the genetic algorithm explored potential variations, refining recommendations over successive iterations. The performance was evaluated on multiple metrics, including accuracy of career path matching, computation time, and memory usage. The dataset was split into training (70%) and testing (30%) sets. The D-GA algorithm was then applied to predict optimal career paths based on this data. Dijkstra's algorithm was used to compute initial shortest career paths, while the genetic algorithm explored potential variations, refining recommendations over successive iterations. The performance was evaluated on multiple metrics, including accuracy of career path matching, computation time, and memory usage. Figure 3 shows the performance comparison before and after the optimization of the algorithm, Continuous features, such as GPA and job offer salary, were normalized to bring all attributes onto a similar scale, ensuring that no single attribute disproportionately influenced the algorithm.

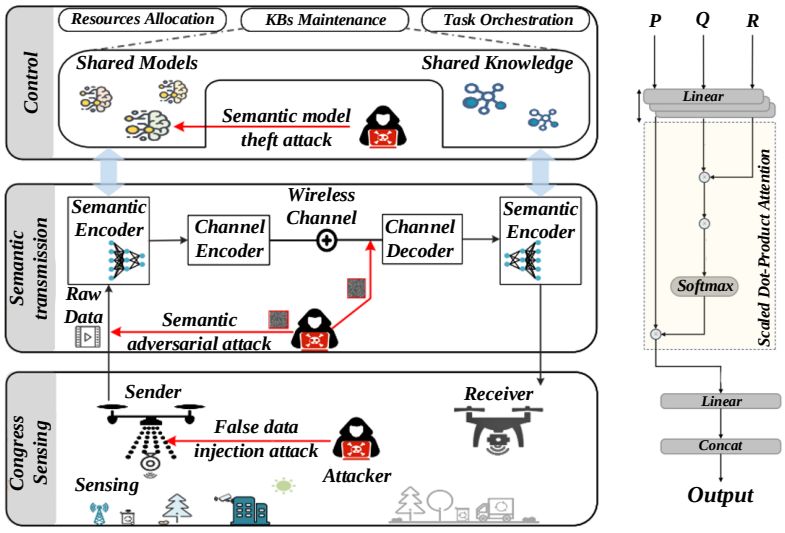

Figure 3: Performance comparison before and after algorithm optimization

Categorical variables like academic major and industry interest were encoded using one-hot encoding, while ordinal features such as job satisfaction were assigned numerical values. Only the most relevant features, such as skills, academic background, and career goals, were retained to reduce noise and improve the efficiency of the algorithm. Figure 3 highlights the tangible benefits of optimizing the career planning system through the D-GA. The improvements in accuracy, reduction in computation time, and enhanced user satisfaction underscore the effectiveness of this hybrid approach. Such enhancements not only make the system more robust but also align it more closely with the needs of college students, facilitating more informed career choices. These factors in terms of gender, family background, and personal ability all affect the employment choices of graduates. Therefore, this section analyzes the employment patterns of students from different backgrounds in three main areas. Table 1 shows the performance comparison of the seed clustering algorithms, in order to distinguish the employment patterns of students with different professional abilities and family

backgrounds, students with good academic performance generally choose to continue their studies and the proportion of those who choose to go abroad for further study is small. In order to avoid the above situation of the genetic algorithm, so that the genetic algorithm does not converge prematurely and produce the phenomenon of early maturity, in this research, this paper adopts the adaptive crossover operator, that is, the crossover operator is no longer fixed, and can be adjusted adaptively with the changes in the population.

Table 1: Performance comparison of clustering algorithms

Clustering algorithm	Contour coefficient	Time (s)
K-means partitioning clustering algorithm	0.415	0.085
Cohesive hierarchical clustering algorithm	0.360	0.069
DBSCAN density clustering algorithm	0.029	0.013

A crucial aspect of configuring a genetic algorithm involves establishing its termination criteria. This entails defining the conditions under which the solution produced by the algorithm is deemed acceptable within the problem domain. Additionally, if the genetic algorithm fails to find a suitable solution, it is essential to establish a maximum number of generations for iterations. This means the algorithm should cease operation after reaching a specified number of generations, regardless of whether the solution is optimal, to avoid unnecessary expenditure of time and resources. The selection of these termination conditions plays a significant role in the efficiency of the genetic algorithm and the quality of the outcomes. If the termination criteria are not aligned with the actual circumstances, even a well-crafted genetic operation may not yield satisfactory results. Figure 4 shows the assessment of the match between students' interests and careers.

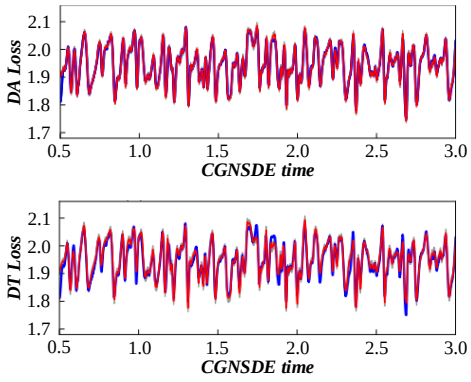

Figure 4: Assessment of student interests and career match

4 Design and implementation of optimization model for students' career planning based on Dijkstra's Algorithm

The Graduate Employment Recommendation section is designed to calculate the students' ratings of employment organizations, and then recommend employment organizations to the students according to the ratings from high to low. Graduates' ratings of employment units consisted of three main components: group employment unit choice, students' preferences for employment unit attributes, and students' preferences for employment unit location. Figure 5 shows the career path shortest distance assessment map, and the group employment unit selection is solved by the traditional BPR algorithm. Then students' preferences for employment unit attributes are incorporated into the solution objective of the BPR algorithm to obtain a new optimization objective function. A binary Gaussian distribution is used to fit the student preference function for the location. The last section of this chapter describes the process of solving the objective function using stochastic gradient descent method. Dijkstra's algorithm is a classical algorithm used to find the student career plan. The algorithm uses breadth-first search to compute the student career plan from any node in a non-negative weighted directed graph to any other store node, i.e., the single-source student career planning problem.

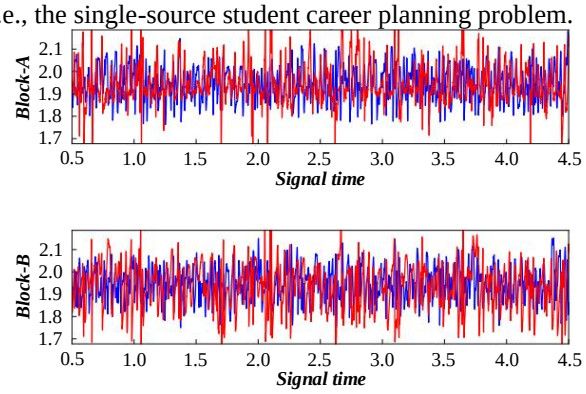

Figure 5: Assessment of shortest distance for career paths

Dijkstra's algorithm is currently extensively utilized and has established itself as a fundamental theory for addressing students' career planning challenges. Researchers frequently adapt Dijkstra's algorithm to suit the specific issues they encounter while investigating these types of problems. The core concept of Dijkstra's algorithm can be summarized as follows: it involves a set represented by S, which initially contains only the source point, S0. The algorithm subsequently adds the shortest paths to the set S from the remaining vertices, denoted as V-S. The set S represents the vertices for which the shortest paths have been identified. Initially, the set S consists solely of the source point S0, which then extends to each point, progressively adding the point with the shortest path to S and designating the remaining points as V-S. This process continues until a comprehensive career plan for a student

is formulated, with the relevant points being included in S and removed from V-S until all nodes in the directed graph are incorporated into S, signaling the completion of the algorithm.

Throughout the execution of the algorithm, it is ensured that the shortest distance from the source point S0 to each vertex in S remains less than or equal to the distance from S0 to any vertex in V-S. In its most straightforward application, Dijkstra's algorithm primarily focuses on the distances between nodes, represented by the weights of the directed graph. However, in practical scenarios such as logistics, distribution, and bus routing problems, it becomes increasingly crucial to consider the time and costs associated with transporting goods or individuals between various nodes. In this research, this paper also improves the traditional Dijkstra's algorithm, which is finally applied with the students' occupation in water. In nature, a variety of biological generations, similar but different, the children inherited the advantages of the father's generation, in the process of biological reproduction, left behind is always high quality, those less adaptable must be eliminated in the competition, that is, the survival of the fittest. At present, the scope of application of genetic algorithm has been quite extensive, due to the good parallelism of genetic algorithm, suitable for solving complex nonlinear problems, has been applied with combinatorial optimization problems, artificial intelligence very popular research direction in the field of computer. The specific content of genetic algorithm can be described as follows: imitating the situation of biological evolution in nature, modeling the problem to be solved as a biological population, choosing a certain coding technique to code the population, and determining the initialized population size, in nature, chromosomes are the most basic representation of biological characteristics, different chromosomes can be combined into different biological characteristics, usually, in the case of the When coding, the coding methods that can be chosen are binary coding, decimal coding and so on. First of all, a group of individuals of a certain size is randomly generated, and the individual with good fitness is superior, so that the new generation of individuals will be more adapted to the environment compared with the individuals of the parent generation, and the confusion matrix of the classification results is shown in Table 2.

Table 2: Confusion matrix for classification results

The real situation	Standard practice	Projected results Counter-example
Standard practice	TP (true example)	FN (false negative)
Counter-example	FP (false positive)	TN (true counterexample)

In the application process of genetic algorithm, the original genetic is considered to select random individuals, while in the D-GA algorithm, this paper adopts the idea, which plays well with the advantages of Dijkstra algorithm, in addition, in the specific implementation of genetic algorithms, some improvements are also made, the specific enhancements are outlined as follows: the design of student career paths aligns with the adaptation function. The initial population is generated based on the principles of Dijkstra's algorithm. This involves executing selection, crossover, and mutation processes on the initial population, utilizing an adaptive crossover method during the crossover phase. Unlike traditional genetic algorithms that often employ random methods to establish the initial population—an approach that can lack direction—Dijkstra's algorithm focuses on identifying the path with the lowest cost and the subsequent node that completes the current shortest route. In the context of the student career paths explored in this project, this means identifying a group that optimally schedules hydraulic resources at minimal cost. Figure 6 illustrates the evaluation of student skills against job requirements, significantly reducing the randomness associated with the original algorithm.

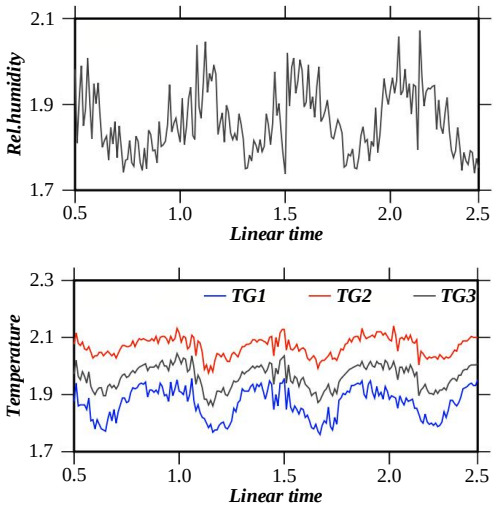

Figure 6: Assessment of student skills and job requirements

According to these constraints to solve the solution of the objective function, and then optimization combined with the actual conditions to finally get the optimal scheduling plan suitable for the student occupation. In the genetic algorithm, this paper refers to the fitness function, the individuals in the group are determined by the fitness function, i.e., it can be calculated which individuals have better adaptability and which individuals should be eliminated. It can be said that the significance of the fitness function in the genetic algorithm is irreplaceable, and the goodness of the fitness function can ultimately determine whether the solution obtained by the genetic algorithm can satisfy the problem domain, which determines the quality of the optimal solution obtained. Figure 7 is assessment of frequency of visits to career development nodes, in summary, all the calculations and judgments are centered around the fitness function. Moreover, the fitness function does not have too many constraints, it does not need to be continuous or derivable, but it must be guaranteed that the

function value is non-negative in the problem domain, so that it is possible to judge and compare the fitness function values of different individuals.

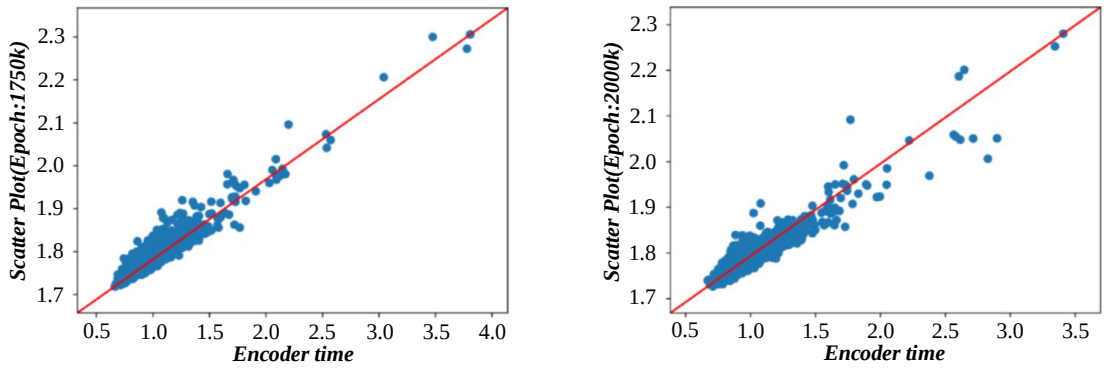

Figure 7: Assessment of frequency of visits to career development nodes

In the process of student occupation scheduling, to assess the benefit of scheduling stage, the benefit is usually calculated based on the objective function, in general, the objective function can be set up one, or can be a group of functions composed of multiple functions. Some of the role of the student occupation is targeted, in this study, this paper chooses to ensure that the maximum amount of power generation can be used as the ultimate goal, in addition to setting some auxiliary constraint functions. In general, after analyzing and studying the requirements of the fitness function as a genetic algorithm, and make appropriate improvements to the objective function, for example, to meet the non-negativity of the fitness function and other requirements, in order to more closely match the implementation of the genetic algorithm. In the research process of this project, this paper adopts the sequence of state information that represents the state information of students' career planning to describe the scheduling decision information of students' careers for the specific content of students' careers. In nature, chromosomes are considered to represent the characteristics of life, therefore, in the process of student career scheduling, the sequence information that represents the planning state corresponds to the chromosomes in biological evolution. Figure 8 shows the graph of students' background and industry demand assessment, therefore, the process of applying genetic algorithms to the scheduling of students' careers can be thought of as follows: first, that size are selected, which serve as the initial population, in student careers, would mean selecting a certain size of the initial planning sequence.

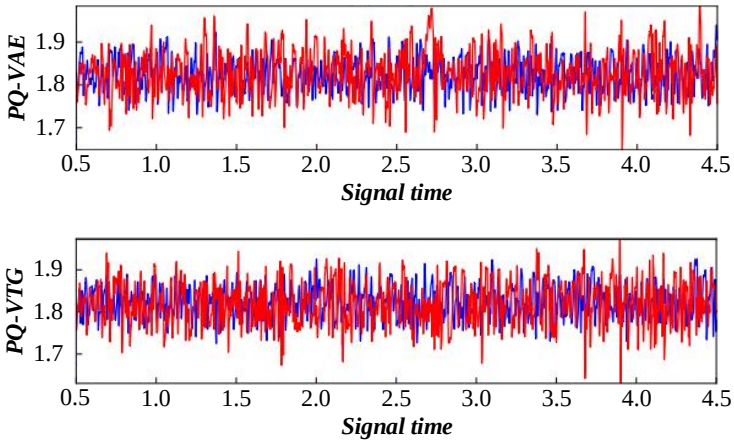

Figure 8: Student background and industry needs assessment

Then the objective function of the student's occupation, and it is obvious that the fitness of the new sequences obtained is higher than that of the parent generation, and in the crossover operation, this paper adopts adaptive crossover algorithm, which improves the efficiency of the algorithm, and the newly obtained sequences are Then the mutation operation is carried out, which improves the diversity of the species, and at the same time, a new generation of population is obtained. Repeat the above steps until the newest generation of population meets the termination conditions of the algorithm. When facing the application process of genetic algorithm, after determining the initial conditions and the fitness function, the first thing to be obtained is the planning sequence, that is, the planning sequence should be expressed into the form of coding. With people's continuous research and study, several encoding methods have been developed that are known to the public,

including binary encoding, decimal encoding, gray code, etc. Among them, binary encoding is the most popular. Among them, binary coding is one of the simplest coding methods. It is also the most widely used at present. Binary coding, as the name suggests, uses only {0,1} for encoding, i.e., all information is represented using only {0,1}. Although binary coding is very simple to understand, but there are some shortcomings and limitations, in the face of some complex problems, the ability of binary coding appears to be somewhat insufficient, cannot well respond to the root of the problem, in the application, with the help of other coding features and binary coding is simple and easy to implement the characteristics. It still retains the simple and easy to understand the characteristics of binary coding, at the same time the binary coding is extended, broadening the field of application.

5 Experimental analysis

A framework for a personalized preference-based graduate employment recommendation algorithm is demonstrated, Figure 9 shows the preference assessment map for career planning path selection, and then calculates the employment choice of the student group by referring to the results of the group delineation; and finally calculates the graduates' scores.

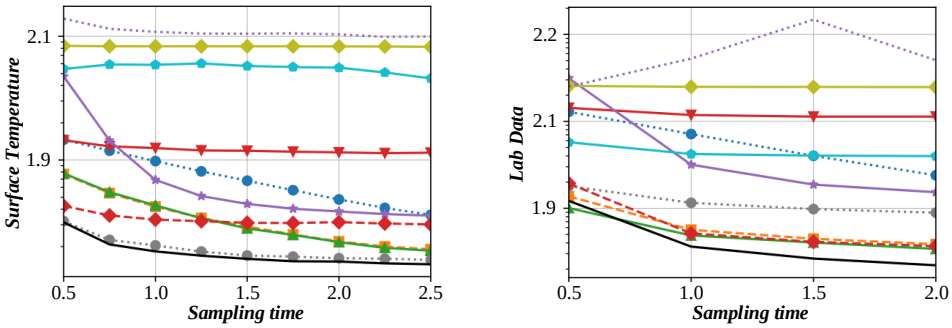

Figure 9: Career planning pathway selection preference assessment

It was analyzed that there are great differences in the employment choices of students with different academic performances and family economic conditions. Therefore, the academic performance and family economic conditions of graduates are selected as the reference characteristics for the division of student groups. The distribution of graduates' family economic condition index and academic performance index is shown. Figure 10 shows the evaluation of the analysis of students' career change cost, the problem is an unsupervised learning, so the clustering method is used to divide the groups. Dijkstra's algorithm, with its space complexity, requires considerable memory, especially when applied to large graphs. The D-GA, while introducing additional storage requirements for multiple candidate solutions (population), is designed to work efficiently in parallel, reducing bottlenecks by pruning less relevant solutions over time.

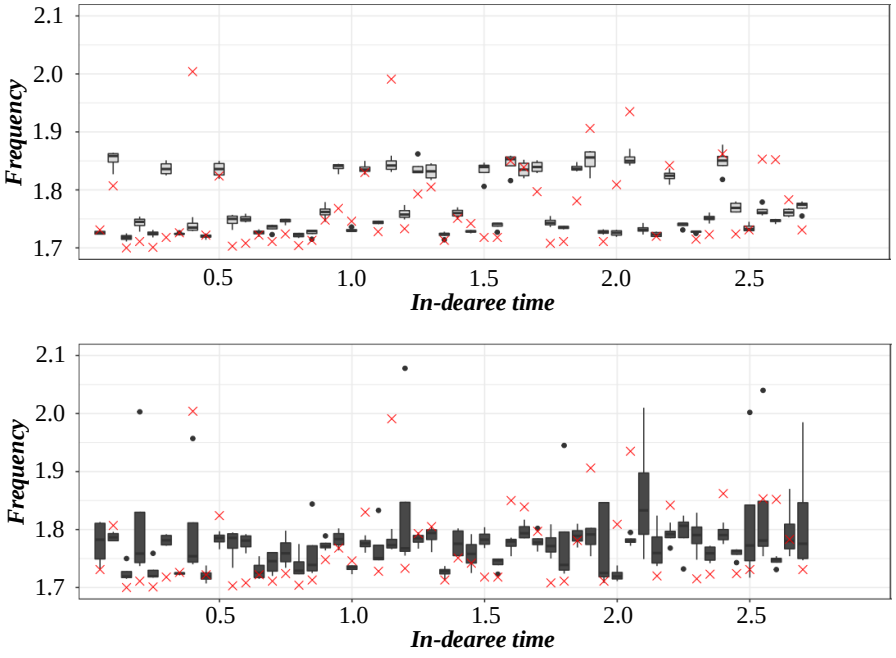

Figure 10: Evaluation of students' career change cost analysis

The D-GA hybrid balances Dijkstra's efficiency in finding the shortest paths with the exploratory capabilities of Genetic Algorithm (GA). While Dijkstra alone computes the shortest path quickly, it can struggle with scalability in large datasets. The D-GA introduces population-based search, which increases computation time due to crossover and mutation steps, but it ultimately reduces the number of iterations needed by optimizing paths dynamically. Figure 11 shows the assessment of students' career planning decisions, while the cohesive hierarchical clustering algorithm and the DBSCAN algorithm do not divide the data samples, and the distinction between academic performance and family economic conditions is not obvious between some groups, especially in the case of the DBSCAN algorithm, which has no obvious distinction between the groups and the division is not homogeneous.

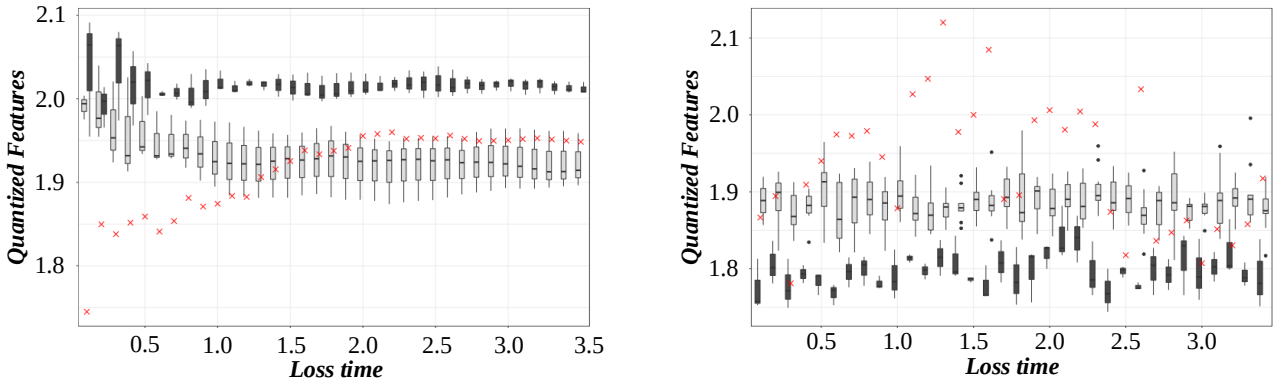

Figure 11: Assessment of student career planning decisions

Therefore, this study uses k-means clustering algorithm to classify student groups. Graduates' ratings of employment units consist of three main components: group employment unit choice, students' preferences for employment unit attributes, and students' preferences for employment unit location. Group employment unit choice indicates the group's rating of the employment unit. Employment unit attribute preference indicates graduates' preference for some specific employment unit characteristics; for example, some students prefer stable careers such as teachers and civil servants, while others prefer positions requiring high professional competence such as engineering and technology. Figure 12 shows the graph of the assessment of the association between career advancement speed and educational background, which is used in this paper to solve the group employment choice using Bayesian personalized ranking strategy.

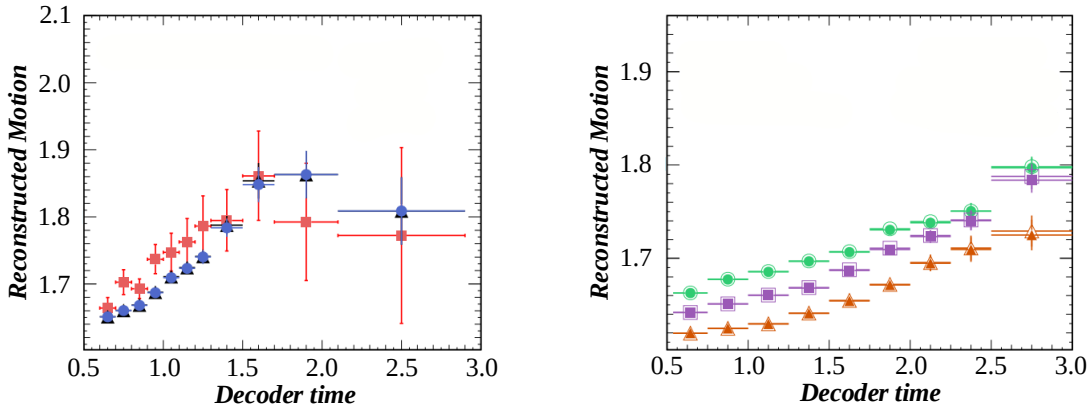

Figure 12: Assessment of the association between speed of career advancement and educational background

6 Conclusion

Dijkstra algorithm is a classical algorithm for finding college students' career planning. It adopts a breadth-first search to calculate college students' career planning from any node in the non-negatively weighted directed graph to any other storage node, the single-source student career planning problem. The Dijkstra algorithm has been widely used and has become a fundamental theory. This paper analyzes some problems in students' career planning, analyzes some existing optimization measures, and establishes a mathematical model for problems related to optimization models in combination with mathematical modelling. The Dijkstra algorithm efficiently finds the shortest path in graphs with non-negative weights, making it highly reliable in structured problems. However, its greedy nature limits its ability to adapt to complex, evolving datasets, such as those encountered in career planning. It works best in static environments but

struggles when dealing with larger, dynamic datasets. The D-GA combines the precision of Dijkstra's algorithm with the exploratory power of GA. This integration allows D-GA to quickly narrow down optimal solutions through Dijkstra's efficient traversal, while GA's population-based approach ensures that it explores a wider range of possibilities. This results in faster convergence and better performance in dynamic environments like career planning systems. By balancing Dijkstra's exactness and GA's adaptability, D-GA outperforms both in terms of efficiency, scalability, and accuracy, making it ideal for personalized and evolving career recommendation systems.

Among the students who chose employment companies, the most significant proportion of students chose other enterprises, about 31 per cent, followed by students who chose state-owned enterprises, about 16 per cent. After graduation, about 80% of students choose to work in computer-related jobs, of which about 62% choose to work in development, and about 17% choose to work in other professional and technical personnel. Among other non-computer jobs, clerical and related personnel accounted for the largest share at 7.8%. Students chose a wide range of industries as employment units, covering 16 industries. Among them, about 63 per cent of students choose to work in industry, followed by a large number in manufacturing, accounting for about 8.8%. The number of college students who chose the remaining 14 fields was small, less than 5 per cent.

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Congestion Control of Large-Scale Elevator Terminal Data Access in Large Metro Stations Based on The Internet of Things

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Keywords: hybrid access method, internet of things, congestion control, ACB control parameters

Received: July 6, 2024

Large metro station IoTs used to face congestion while access to terminals was going on a large scale. Due to this, low success rate in access and delay in monitoring critical equipment was observed, which included elevators and escalators. This paper presented a congestion control method for large-scale elevator terminal data access in metro stations using IoT. Business data were categorized based on volume and latency requirements: Slot ALOHA (SA) direct access mode was used for delay-insensitive, small data services, and Access Class Barring (ACB) random access was used for time-sensitive, large data services. ACB control parameters were dynamically adjusted by estimating access requests. Using uniform and Beta distribution models, the method's effectiveness was validated through experiments. With 4000 access requests, the hybrid method achieved a 52.43% success rate and a 76.72 ms average delay under the uniform model, and a 42.07% success rate with an 82.02 ms average delay under the Beta model. These results demonstrated the method's ability to meet Quality of Service (QoS) requirements for high-priority services, ensuring efficient and reliable communication in large-scale IoT environments.

Povzetek: Prispevek predstavlja hibridno metodo za nadzor preobremenjenosti do podatkov naprav IoT, ki uporablja kombinacijo direktnega in naključnega dostopa, s prilagajanjem parametrov glede na obseg zahtev.

1 Introduction

Based on the current urban development and people's travel needs, the number of elevators inside large metro stations is also growing [1]. The stability of elevator operation is closely related to the safety of residents. However, due to the quality, maintenance, supervision, and other influencing factors, elevator accidents often occur. How to conduct unified real-time monitoring of elevator equipment in large and medium-sized Spaces to reduce daily lightweight failures and prevent heavyweight accidents has become a hot topic of scholarly attention [2, 3].

The increasing global population and urbanization have heightened the demand for elevators, necessitating advanced, safe, and efficient systems. China’s elevator demand grows by 5%–7% annually due to the need to replace outdated units and comply with new regulations, increasing maintenance workloads and risks. Innovative designs must prioritize safety, including weight capacity, emergency alarms, and secure installation sites. Energy-efficient elevators can reduce operational costs significantly. Traditional monitoring systems, like video surveillance, fail to reflect the elevator's condition and failure rates adequately. With its advantages of low power consumption, significant connection, low delay, and high reliability, the Internet of Things (IoT) can realize the transmission and processing of multiple types and large-scale data [4].

Based on this, some scholars use IoT technology to monitor elevators' operating status data, dramatically improving elevator operation security and effectively reducing equipment operation and maintenance costs. Mao et al. [5] discussed the integration of Internet of Things (IoT) technology to enhance the remote security management of elevators, addressing the associated safety risks. They proposed an IoT-based architecture for elevator fault diagnosis and maintenance. The study established a fault diagnosis management system centered on IoT, outlining maintenance methods to ensure the safety and stability of elevator operations. This approach aims to improve the overall security and efficiency of urban transportation through advanced technology. Lai et al. [6] adopt the more predictive state maintenance method to realize the remote monitoring of highly distributed elevator equipment status, effectively improving the safety and reliability of equipment operation.

IoT devices, ranging from consumer products to industrial components, are becoming ubiquitous, driving the concept of "Smart homes" with enhanced safety and energy efficiency. Wearable fitness and health monitors, network-enabled medical devices, and smart traffic systems contribute to “smart cities” that reduce congestion and energy use. IoT also promises to improve the independence and quality of life for people with

disabilities and the elderly. The impact of IoT extends to agriculture, industry, and energy sectors, enhancing information flow along the production value chain. Companies and research organizations predict significant economic effects [7]. A market research report revealed that the global IoT market was valued at $1.90 billion in 2018 and is projected to grow to $11.03 billion by 2026. Additionally, the European Union (EU), the United States (USA), China, and other nations have developed IoT-related action plans. These initiatives include the IoT-An Action Plan for Europe and various IoT development plans for the years 2016–2020 [8].

Song et al. [9] discussed the adoption of smart technologies and networking solutions like the Internet of Things (IoT) by leading cities in China to enhance economic opportunities and global climate resilience. They presented the smart city concept as a complex system integrating sensors, data, applications, and organizational forms to make cities more agile and sustainable. The paper provided a comprehensive assessment of smart city initiatives in China, classifying practices into six key dimensions: energy, agriculture, transport, buildings, urban services, and urban security operations. Chinese smart city policies and practices aim to explore renewable energy, improve public convenience, and enhance urban comfort and citizen friendliness. The study also addressed concerns in areas such as system integration, governance, innovation, and finance. A policy vision was outlined to build public-private collaborative networks, encourage innovation and investment in smart city initiatives, and emphasize smart services.

In practical applications, the infrastructure of the wireless cellular network is relatively perfect, the coverage area is comprehensive, and the security is high, which is one of the leading carrying networks of IoT communication. However, the original intention of traditional wireless cellular network design is to deal with the communication problem between humans and humans (H2H), and there are some differences in the communication characteristics between machine to machine (M2M). Machine-type communication (MTC) devices, integral to Industry 4.0, support smart factories, healthcare, and surveillance by generating data and making policy-based decisions. The demand for these devices is projected to reach 50 billion by 2025. These devices require robust security due to their vulnerability and usage in open environments. Lightweight cryptography is the preferred solution for MTC devices due to their limited computational and memory capacities. This cryptographic approach ensures strong encryption while being efficient and cost-effective, enhancing security for the growing number of IoT devices. MTC devices are autonomous and central to automating IoT frameworks, evolving to support the advancements of Industry 4.0. They form Machine-to-Machine (M2M) communication networks, also known as cyber-physical systems and edge nodes, creating an autonomous system of resource-constrained devices [10].

The six key features of Machine Type Communication (MTC) in 6G are ultra-low latency and high reliability, massive connectivity, energy efficiency, scalable and flexible network architecture, enhanced security and privacy, and advanced AI and machine learning integration. These features ensure instantaneous and reliable data transmission for critical applications, support billions of IoT devices, extend the battery life of remote sensors, allow dynamic resource allocation, protect sensitive data, and optimize network performance through predictive maintenance and anomaly detection. These features collectively create an efficient, reliable, and secure communication environment for the 6G era [11].

Due to the limitation of channel resources, when the IoT at metro stations has a large number of elevators, and other equipment data access, the time delay indicator of the system is higher, and the throughput will decrease significantly. Therefore, there is a great demand for a large-scale terminal access algorithm tailored to the communication characteristics of the IoT at large metro stations to ensure the reliable transmission of information data of crucial equipment. In response to the above issues, Chou et al. [12] used Bayesian theory to estimate the number of access applications, preamble code conflict rate, and the number of following time-slot applications at the current time-slot. Furthermore, the optimal ACB control parameters are discussed by judging the number of applications for the subsequent access time slot through quantitative prediction methods. The scheme is based on the premise that the current time-slot access conflict makes direct rebleeding at the next time-slot, with some error from the system of refeeding in the actual access process.

Zhang et al. [13] addressed the growing need for improved communication content and quality in the context of advancing network and communication technologies. This research concerns the optimal data collection and path planning of multi-unmanned aerial vehicle (UAV) to achieve extensive terminal accessibility in IoT scenarios. The novelty of the approach consists of integrating sensor area partitioning with the flight trajectory planning of multiple UAVs with the main objectives of load balancing while the overall completion time for the tasks at hand is minimized. A novel k-means algorithm has been developed to balance the quantity of data in each cluster. Accordingly, the flight trajectories of the UAVs were represented discretely by an enhanced genetic algorithm including the 2-opt optimization operator for solving the multiple traveling salesman problem (MTSP) problem, improving the computational effectiveness. Extensive simulations have validated the efficiency of the suggested approach in smoothing out the imbalances in the distribution of tasks among UAVs and significantly reducing the duration of tasks. The convergence rate for this methodology was higher than the conventional genetic algorithm; hence, this proved that it was computationally efficient. Equipped with a new, efficient methodology for multi-UAV-assisted IoT terminal data gathering, it brings balance and efficiency in task distribution, unfolding the full power of professional algorithm solutions when acquiring optimal results in more complicated engineering scenarios.

Varsha et al.[14] proposed an innovative intelligent traffic management system for wireless cellular networks to enhance M2M connections, pivotal for IoT. They focused on improving Access Class Barring (ACB), a method traditionally relying on a static factor to manage machine-type communication device (MTCD) traffic. The study introduced a Bayesian inference-based learning automatons (BI-LA) approach that dynamically adjusts the ACB factor. This system leverages learning automata's self-adaptive learning to estimate and manage M2M traffic more effectively. By framing the problem around collision probability and using Bayesian inference to adapt the ACB factor, the proposed method was tested using network simulator-3 (NS3). The performance metrics—average access delay, access attempts, access success rate, and access success—demonstrated that the BI-LA ACB technique outperformed traditional and contemporary ACB methods, achieving minimal access delays of approximately 1876 ms and 27.6 ms.

The main problem arises due to a large amount of UEs present in the RA techniques, as discussed by Piao and Lee [15], where increased collisions and delays arise. They propose a new RA scheme that combines four-step RA with two-step RA, based on the 3rd Generation Partnership Project Release 16. This work tries to avoid a conflict with the available RA resource, then achieves a better performance of efficiency and brings down the average RA delay. This solution aims to optimize the two-step RA probability and thus provides a resource configuration and parameter setting algorithm that allows the UEs to carry out both RA methods simultaneously. Then, the authors proved further that the proposed approach is valid using a Markov chain model. The proposed approach also has its potential confirmed in extensive comprehensive simulations on supporting RA procedures in the case of massive and heterogeneous device access for 5G and 6G communication applications.

Yu et al. [16] investigated the performance of massive machine-type communications (mMTC) in status update systems, where numerous machine-type communication devices (MTCDs) send status packets to a base station (BS) for system monitoring. The authors identified that packet collisions due to massive MTCDs negatively impact status update performance. To address this, they proposed a joint access control, frame division, and subchannel allocation scheme. They first analyzed access control, packet collisions, and packet errors, deriving a closed-form expression of the average age of information for all MTCDs as a performance metric. Their proposed scheme was shown through simulations and numerical results to achieve near-optimal performance, comparable to exhaustive search methods, and outperformed benchmark schemes. Bui et al. [17] present an access protocol based on distributed queue (DQ) mechanisms to deal with M2M communication large-scale access problems for cellular networks. To maximize the DQ mechanism performance, first of all, the base station in the random-access opportunities is roughly the number of conflict detection equipment to avoid excessive division of DQ. Then based on the probing results, the base station randomly divides the device into a determined number of groups and "pushes" these groups to the end of the logical access queue. Finally, the validity and feasibility of the proposed protocol are verified by simulation.

Congestion control and optimization methods overview in IoT applications-the methodologies, the datasets used, the results, and the limitations are represented in Table 1. This comparison identifies the gaps that this paper will address with the proposed hybrid access method.

Table 1: Summary of related works on congestion control and access optimization Methods in IoT applications highlighting limitations and positioning the hybrid access method as a novel solution

Study	Method	Datasets	Key Results	Limitations
Mao et al. [5]	IoT-based architecture for fault diagnosis	Elevator operational data	Improved safety and stability of elevator operations through IoT monitoring	Limited scope to fault diagnosis only
Lai et al. [6]	Predictive maintenance with IoT integration	Distributed elevator equipment data	Enhanced safety and reliability of elevator systems	Focused only on maintenance, lacks scalability analysis
Chou et al. [12]	Bayesian theory-based ACB optimization	Simulated data	Improved ACB parameters, reduced conflict rate	Errors in real-time predictions
Zhang et al. [13]	Multi-UAV data collection and path optimization	Simulated IoT scenarios	Balanced task distribution, reduced completion time	High computational overhead
Varsha et al.[14]	Learning Automaton-based ACB scheme (LA-ACB)	Cellular Base Station data	Controlled M2M data, reduced H2H interference	High implementation complexity
Piao and Lee [15]	Integrated 2-4 step Random Access (RA) methods	Cellular network simulations	Reduced collisions and delays	Limited to specific RA configurations

Bui et al. [17]	Distributed Queue (DQ)-based access protocol	LTE/LTE-A network data	Reduced congestion, improved success rate	Requires precise group partitioning

This paper proposes a hybrid access methodology that combines Slot ALOHA with Access Class Barring for large-scale IoT scenarios in metropolitan transit stations. The proposed methodology, by dynamically changing ACB control parameters and implementing predictive modeling on access requests, should be able to provide high QoS for important applications like elevator monitoring under different traffic conditions. This novel strategy overcomes some fundamental limitations of the previous approaches by providing a scalable, reliable, and economic solution to congestion management in IoT systems with complex networks. Therefore, the key contributions of the paper are as follows:

The key contributions of the paper are as follows:

1. **Congestion control method**: Developed a method for managing large-scale elevator terminal data access in metro stations using IoT, addressing low access success rates and delays.
2. **Data categorization**: Divided business data based on volume and latency requirements, using Slot ALOHA (SA) for delay-insensitive data and Access Class Barring (ACB) for time-sensitive data.
3. **Dynamic ACB adjustment**: Proposed dynamically adjusting ACB control parameters by estimating access requests to optimize terminal access.
4. **Performance evaluation**: Demonstrated through simulations that the hybrid access method improves access success rates and reduces delays, especially with high access requests.
5. **Application in IoT environments**: Ensured Quality of Service (QoS) for high-priority services in large-scale IoT environments in metro stations.
6. **Predictive access application**: Developed a method to predict access applications for better access control.
7. **Experimental validation:** Validated the method in a Shanghai metro station, showing practical advantages over traditional methods.

2 Systems model and custom MAC layer protocol for IoT communication in large metro stations

2.1 Systems model

Based on the practical application, a metro station communication model is built with large-scale MTCD to simulate the congestion caused by frequent network access by communication devices. Illustration of IoT communication model for large metro stations in Fig. 1 shows how the MTCDs will be sending their data to the server via the eNB.

The evolved Node B (eNB) receives, controls, and allocates up/down dynamic resources. MTCD data is transmitted to a fixed gateway through the narrowband IoT, which forwards the data to the server. In the IoT model, when two or more MTCDs use the same preamble code simultaneously, it indicates that the decision is in conflict and the device access fails.

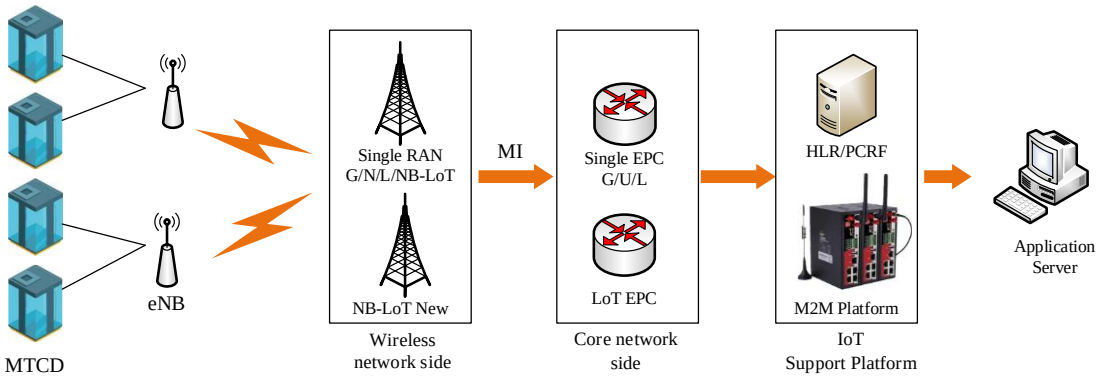

Figure 1: Illustration of the IoT communication model for large metro stations, showcasing the flow of data from MTCDs to servers via the eNBCustom MAC Layer Protocol

Given that complex signaling can reduce the success rate of device access, the network employs the Media Access Control (MAC) protocol [18]. The MAC layer protocol combines Selective Acknowledgement (SA) and Access Class Barring (ACB) controls to adapt to various types of business data and enhance access speed and success. For services with small amounts of valid data and low sensitivity to delay, SA direct access is utilized. Conversely, ACB random access is applied to delay-sensitive and data-intensive services. Fig. 2 illustrates the hybrid MAC layer protocol diagram, where T_i is the i-th access timeslot.

The hybrid MAC layer protocol divides each incoming data packet into four parts:

1. Broadcasting data access information and ACB control parameters for the current timeslot.
2. Assigning preamble codes to randomly accessed services.
3. Handling SA direct access business.
4. Conducting data transmission.

Using the hybrid MAC layer protocol for the classified transmission of different business data effectively reduces signaling consumption, accelerates data access, and ensures the Quality of Service (QoS) demands of high-priority business services.

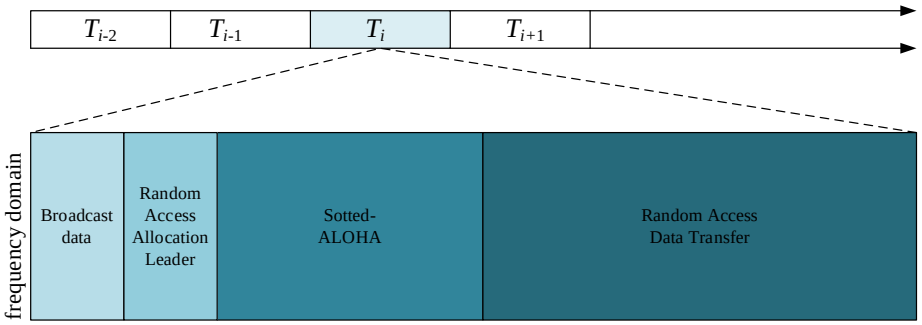

Figure 2: Hybrid MAC layer protocol

3 Design of hybrid access method

3.1 SA method and improvement

The SA transmits data by speaking first. Signal overlap is likely to occur during concurrent operations, leading to network congestion. Therefore, a random wait period is introduced before attempting to resend the data. The data transmission process is illustrated in Fig. 3.

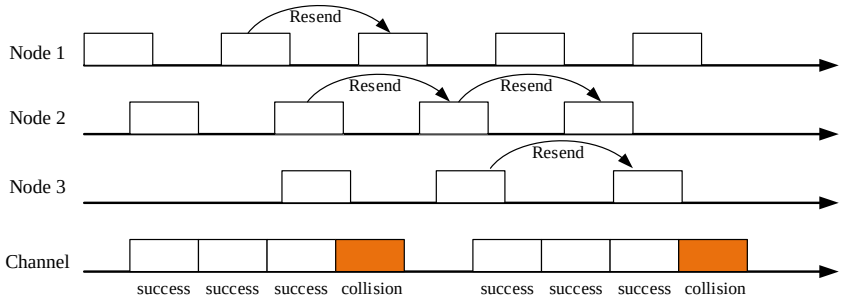

Figure 3: Data sending process for traditional SA method

In the traditional Slot ALOHA (SA) method, the time for retransmission is random, leading to a high probability of complete or partial collisions. This randomness reduces the efficiency of information utilization and decreases system throughput.

To address these issues, the data transmission process has been improved. The transmission period is divided into several time slots, and data can only be sent at the initial point of a time slot. By ensuring that nodes transmit information within their designated time slots, the likelihood of collisions is significantly reduced, as nodes are not transmitting simultaneously. This structured approach allows for more efficient use of the available bandwidth and improves overall system throughput.

The improved SA data-sending process, which mitigates collisions and enhances throughput, is illustrated in Fig. 4. This method ensures that each node's transmission is independent of others, leading to more reliable and orderly communication within the network.

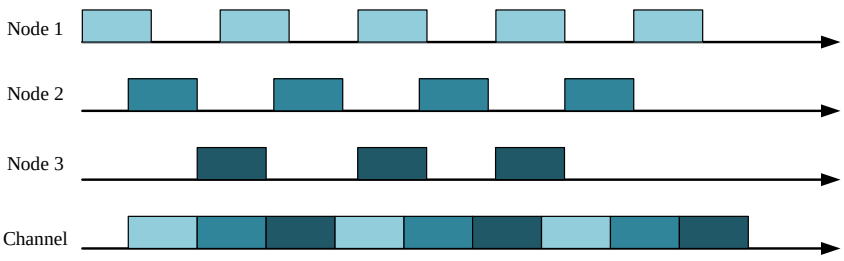

Figure 4: Data sending process for improving the SA method

The relationship between the throughput rate Q and the sent packet quantity G can be expressed as Eq. (1):

$$Q = Ge^{-G} \tag{1}$$

When two nodes transmit within the period T', the data transmission delay function is given in Eq. (2):

$$T_Y = 2T' + t_d + [\varphi T' + (B+1)T'](e^G - 1) \tag{2}$$

Where φ represents the waiting time for a response, t_d represents the propagation duration and B represents the maximum value of the backoff time slot.

The fixed transmission channel and the number of inherent node parameters determine the transmission delay of SA. Therefore, the improved method is only suitable for processing delay-insensitive and small data volume services. Otherwise, the transmission error will increase, and the availability of information will be reduced.

3.2 Estimation of access applications based on time series prediction

3.2.1 Estimation of current timeslot access applications

For services using the ACB (Access Class Barring) random access mode, the application amount of the service should be estimated based on the occupation of the preamble code [19, 20]. Assume that w_i represents the state of the i -th preamble code. The states are defined as follows:

- When $w_i = 1$, the preamble code is not selected and is idle.
- When $w_i = 1$, an MTCD (Machine-Type Communication Device) has selected the preamble code and it is busy.
- When $w_i \geq 2$, two or more MTCDs have selected the preamble code, resulting in a conflict status [21].

The probabilities of the i -th preamble being in these three states is given by the following Eq. (3):

$$P(w_i) = \begin{cases} \left(1 - \frac{1}{N_p}\right)^{n_a}, & w_i = 0 \\ \frac{n_a}{N_p} \cdot \left(1 - \frac{1}{N_p}\right)^{n_a - 1}, & w_i = 1 \\ 1 - \left(1 - \frac{1}{N_p}\right)^{n_a} - \frac{n_a}{N_p} \cdot \left(1 - \frac{1}{N_p}\right)^{n_a - 1}, & w_i \geq 2 \end{cases} \tag{3}$$

Where N_p represents the number of available preamble codes in the current timeslot, n_a indicates the number of access requests for the current timeslot.

Assume that the number of preamble codes satisfying $w_i = 0$, $w_i = 1$, and $w_i \geq 2$ in the current timeslot are L_1, L_2, and L_3, respectively. Then, the maximum likelihood estimation of the number of access applications in the current timeslot is expressed as Eq. (4):

$$P = P(w_i = 0|N_a)^{n_1} \cdot P(w_i = 1|N_a)^{n_2} \cdot P(w_i \geq 2|N_a)^{n_3} \tag{4}$$

The principle is to ensure that the number of access requests in the next time slot is optimal. The estimated number $\widehat{N}_a$ of access requests in the current timeslot can be obtained by setting N_a to the maximum value. The expression is given in Eq. (5):

$$\widehat{N}_a = arg \max \sum_j^J ln\, P(w_j|N_a) \tag{5}$$

After ACB, the comparison results between the maximum likelihood estimate and the actual application amount are shown in Fig. 5. It can be seen from the figure that the trend changes of the two lines are relatively consistent, indicating that the estimated value aligns well with the actual value.

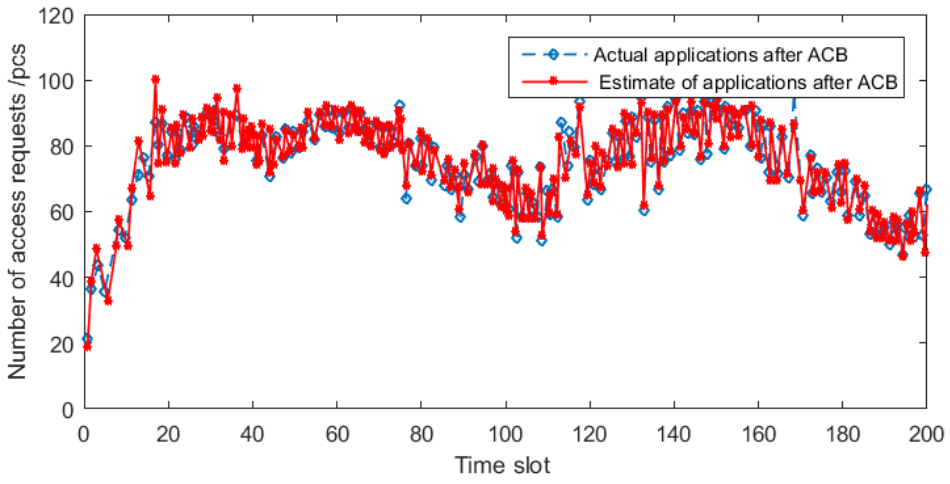

Figure 5: Comparison results of maximum likelihood estimation and actual application volume (After passing the ACB)

According to the maximum likelihood estimation after passing the ACB, the actual number of access applications can be calculated as $\widehat{N} = \widehat{N}_a/a$, where a is the ACB control parameter of the current timeslot. Before passing the ACB, he comparison between the maximum likelihood estimates and the actual number of applications is shown in Fig. 6.

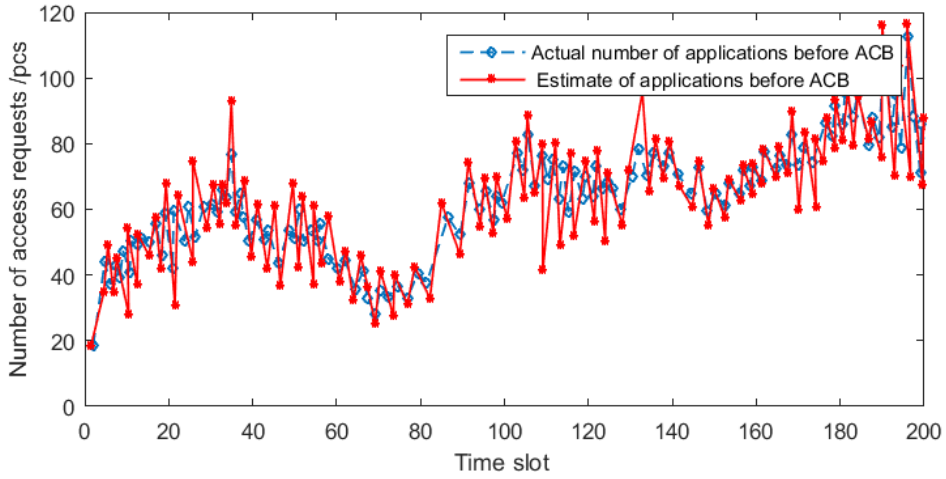

Figure 6: Comparison results of maximum likelihood estimation and actual application volume (Before passing the ACB)

For services accessed in SA mode, the estimation is based on the physical resource block status of the current time slot [22]. Assuming that the total number of available resource blocks is U_s, and the number of idle rate blocks in the current timeslot is $\widetilde{U}_{k,i}$. The actual idle rate is $\tilde{P}_{k,i} = \frac{\widetilde{U}_{k,i}}{U_s}$, the theoretical idle rate is $P_{k,i} = \left(\frac{U_s-1}{U_s}\right)^{C_i}$, where C_i is the access application volume of the current timeslot. y equating the theoretical idle rate to the actual idle rate, $\tilde{P}_{k,i} = P_{k,i}$, the number of access requests in the current time slot is obtained as shown in Eq. (6):

$$\hat{C}_i = \frac{log(\tilde{P}_{k,i})}{log(N_i(N_i-1)} \tag{6}$$

3.2.2 Estimation of next timeslot access applications

Assume that the estimated number of access applications in the i -th time slot is $\widehat{N}_i$, the number of access successes is W_i, the number of newly arrived access applications in the $i+1$ time slot is $T_{i_{+1}}$, and the number of access applications that need to be retransmitted is $H_{i_{+1}}$. Then the estimated number of access applications in the $i+1$ time slot can be shown as Eq. (7):

$$\widehat{N}_{i+1} = \begin{cases} \widehat{N}_i - W_i + H_{i+1} + T_{i+1}, i \le I_D \\ \widehat{N}_i - W_i + H_{i+1}, \qquad i > I_D \end{cases} \tag{7}$$

Where, I_D represents the last timeslot.

Since the access request volume is a time series, the weighted sum of historical increments is used as an increment in the next time slot. The newly arrived access applications in the $i+1$ time slot, $T_{i_{+1}}$ can be expressed as shown in Eq. (8):

$$T_{i_{+1}} = \frac{3}{5}T_i + \frac{3}{10}T_{i-1} + \frac{1}{10}T_{i-2} \tag{8}$$

Because $T_i = \widehat{N}_i - \widehat{N}_{i-1} - H_i + W_{i-1}$, the Eq. (9) is as follows:

$$\begin{aligned} T_{i_{+1}} &= max\left\{0, \quad \left(\tfrac{3}{5}T_i + \tfrac{3}{10}T_{i-1} + \tfrac{1}{10}T_{i-2}\right)\right\} \\ &= max\left\{0, \quad \begin{pmatrix} \tfrac{3}{5}\widehat{N}_i - \tfrac{3}{10}\widehat{N}_{i-1} - \tfrac{2}{10}\widehat{N}_{i-2} - \tfrac{1}{10}\widehat{N}_{i-3} \\ -\tfrac{3}{5}H_i - \tfrac{3}{10}H_{i-1} - \tfrac{1}{10}H_{i-2} + \\ \tfrac{3}{5}W_{i-1} + \tfrac{3}{10}W_{i-2} + \tfrac{1}{10}W_{i-3} \end{pmatrix}\right\} \end{aligned} \tag{9}$$

After transformation, the estimated amount of access requests for the next time slot can be obtained. The expression is given in Eq. (10):

$$\widehat{N}_{i+1} = \begin{cases} max\left\{\widehat{N}_i, \begin{pmatrix} \frac{3}{5}\widehat{N}_i - \frac{3}{10}\widehat{N}_{i-1} - \frac{2}{10}\widehat{N}_{i-2} - \frac{1}{10}\widehat{N}_{i-3} \\ -\frac{3}{5}H_i - \frac{3}{10}H_{i-1} - \frac{1}{10}H_{i-2} + \\ \frac{3}{5}W_{i-1} + \frac{3}{10}W_{i-2} + \frac{1}{10}W_{i-3} \end{pmatrix}\right\} - W_i, i \le I_D \\ \widehat{N}_i - W_i + H_{i+1}, \qquad i > I_D \end{cases} \tag{10}$$

The comparison between the predicted application amount and the actual application amount of the time series is shown in Fig. 7. It can be seen from the figure that the curve change trend of the estimated value and the actual value is relatively consistent, indicating that the predicted result of the access application volume aligns well with the actual value.

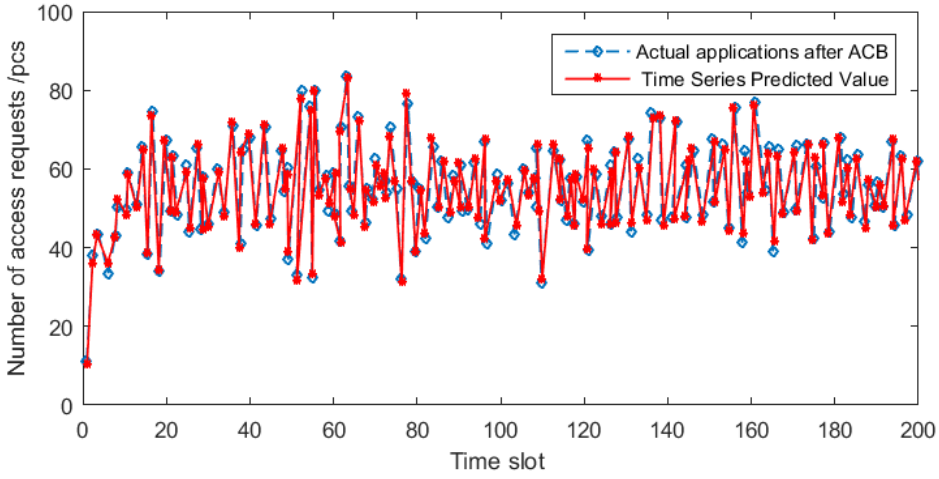

Figure 7: Comparison results of predicted and actual application volumes of time series

3.2.3 Parameter adjustment of predicted values

Update the packet parameter L_1 and ACB control parameter a of the dynamic preamble code according to the prediction value of the service arrival to ensure the access success rate of the next timeslot. Since $w_i = 1$ indicates the successful transmission of the preamble code, the estimated value of the preamble code that can transmit successfully is given in Eq. (11):

$$M[N_s|N_a = n_a] = \sum_{i=1}^{N_p} P(w_i = 1|N_a = n_a) = N_p \cdot C_{n_a}^1 \cdot \frac{1}{N_p} \cdot (1 - \frac{1}{N_p})^{n_a - 1} = n_a \cdot (1 - \frac{1}{N_p})^{n_a - 1} \tag{11}$$

N_s represents the number of preamble codes successfully transmitted, and N_a represents the number of services filtered by ACB. Suppose the system contains N MTCDs, and N_a MTCDs pass the screening. The probability is given in Eq. (12):

$$P(N_a = n_a|N = n) = C_n^{n_a} \cdot a^{n_a} \cdot (1 - a)^{n - n_a} \tag{12}$$

Then the estimated value of success access is given in Eq. (13):

$$M[N_s|N = n] = n \cdot a \cdot (1 - \frac{a}{N_p})^{n_a - 1} \tag{13}$$

Deriving from a, the optimal control parameter is given in Eq. (14):

$$a' = \frac{J}{n} \tag{14}$$

From Eq (14), the access success rate is highest when the number of access requests matches the number of currently available preamble codes. The effect is optimal when L_1 equals the number of high-priority access requests in the current timeslot.

Fig. 8 shows the relationship between the number of access requests and access successes when the number of preamble codes is 35, 60, and 76, further verifying the correctness of the above conclusions.

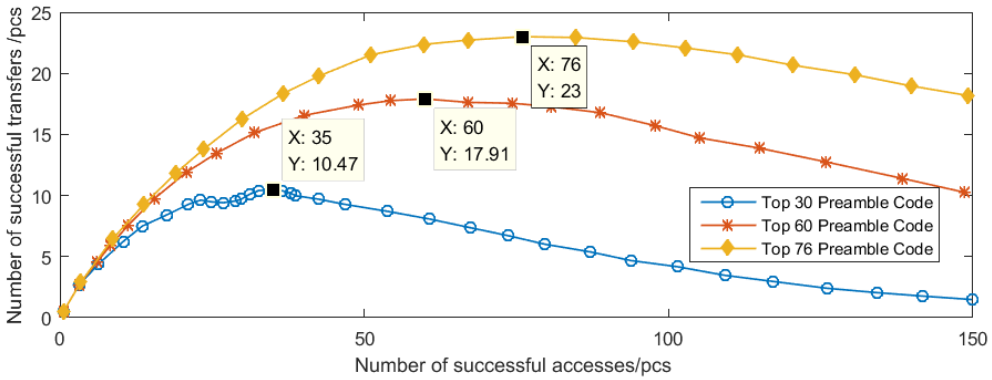

Figure 8: Relationship between access success and access requests

3.3 Hybrid access process

The access process is outlined in Figure 9, illustrating the steps involved in managing access requests for high-priority and low-priority services using the hybrid access method. Here's a detailed explanation of the process:

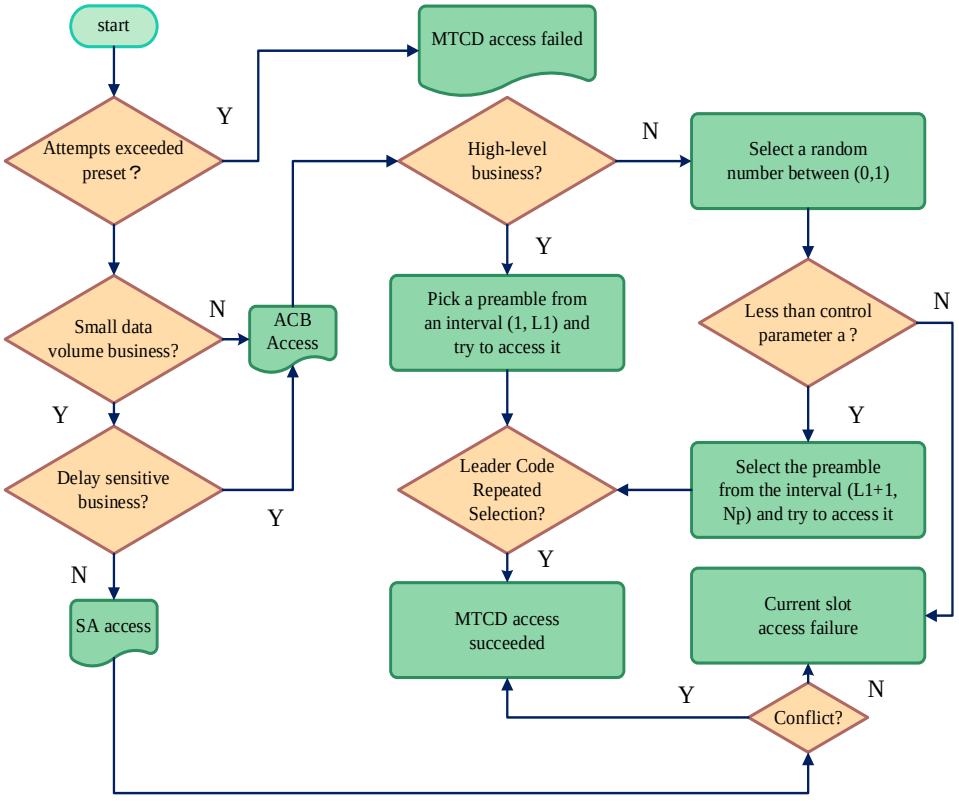

Figure 9: Access flow of the hybrid method

1. **Initial collection and setup:**
   - ❖ The evolved Node B (eNB) collects access data from the previous timeslot, counts the usage of preamble codes, completes channel resource allocation, and sets parameters such as ACB control and backoff parameters.
2. **Random access phase:**
   - ❖ Determine the priority of the application access business:
     - ➢ For high-priority services, the system directly selects a preamble code from the set $K_1[1,\ L_1]$ reserved for high-priority services and proceeds to the access link.
     - ➢ For low-priority services, a random number p is selected from the interval [0,1]. If p is less than the ACB control parameter a of the current timeslot, a preamble is selected from the set $K_2[L_1+1,\ N_p]$ designated for low-priority services. If $p \geq a$, the access is terminated.
3. **Direct access phase:**
   - ❖ Services with small data volumes proceed with direct access.

4. **Data transmission phase:**
   - ❖ MTCDs that have successfully obtained a transmission opportunity begin data transmission.

This structured approach ensures that high-priority services are given precedence and that low-priority services are managed in a way that minimizes conflicts and optimizes resource use. The hybrid access method dynamically adjusts parameters based on historical data, improving overall system throughput and efficiency.

4 Experiments

4.1 Experimental preparation

The experimental site for the study is a large metro station in Shanghai, equipped with a significant number of IoT terminals. The configuration of the parameters used in the experiments including the number of preambles, maximum transmission attempts, conflict resolution time, and escape time, providing a baseline for evaluating the hybrid access method are detailed in Table 2.

Table 2: Key parameters used in the simulation experiments, including preambles and conflict resolution time, forming the baseline for evaluating the hybrid access method

Parameter	Value
Number of preambles	60
Maximum transmission times of preamble code	8
Conflict resolution time	24 ms
Escape time	15 ms

These parameters were utilized to simulate and analyze the performance of the hybrid access method under various traffic conditions, including uniform and beta distribution models, to verify its effectiveness in managing access congestion and ensuring timely data transmission in large-scale IoT environments.

The uniform and beta distribution models are employed to verify the feasibility of the hybrid access method by simulating various types of business data, including periodic and sudden data as well as random and irregular data, in elevator monitoring. To ensure comparability, ACB access and LA-ACB with different parameters are also used as benchmarks in the experiments. These experiments aim to count and compare the average access delay and access success rate of different services [23].

Given that the hybrid access method assigns different ranges of preamble codes according to the priority of services, while the ACB method shares all access resources uniformly, a direct comparison would be unfair. Therefore, the success rate of preamble code access is redefined for a fair assessment. The success rate, P_T, is calculated as the ratio of the number of successfully accessed services (N_c) to the total number of preamble codes used in the access process (N_{all}). This redefinition allows for a more accurate comparison of the efficiency and effectiveness of the hybrid access method against traditional ACB methods.

4.2 Experimental results and analysis

4.2.1 Simulation results and analysis of uniform distribution model

This section discusses the simulation results and analysis using a uniform distribution model to evaluate the performance of the hybrid access method compared to traditional methods such as ACB (Access Class Barring) and LA-ACB (Learning Automata ACB).

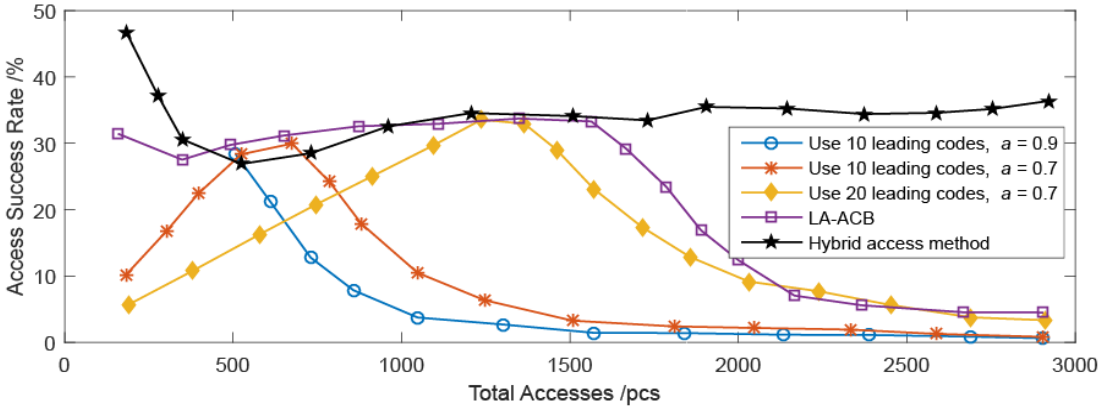

Figure 10: Comparison of access success rates for high-priority services using the hybrid access method, ACB, and LA-ACB under the uniform distribution model

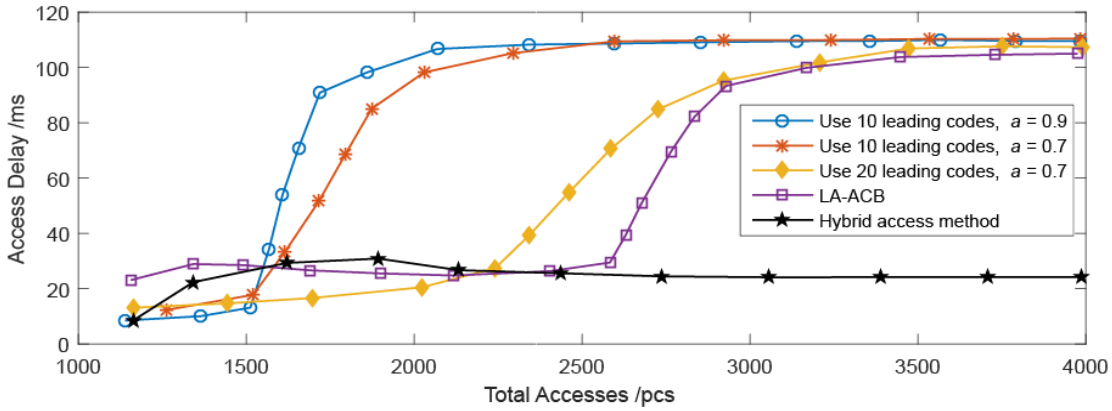

Figure 11: Comparison of average access delay for high-priority services under the uniform distribution model

The access success rate of high-priority services is demonstrated in Fig. 10. When the number of access applications is small, the LA-ACB method performs excellently. However, as the number of applications increases, LA-ACB causes resource wastage, and its performance gradually declines. The hybrid access method initially shows lower success rates and higher delays due to high estimation errors but improves significantly as the number of access applications increases. Precisely, the hybrid method demonstrates a higher success rate as access requests increase, reaching 52.43% at 4000 applications. Fig. 11 shows the comparison of average access delay for high-priority services. With an increase in access applications, the average access delay for the hybrid access method remains relatively stable, indicating higher resource utilization and meeting high-priority service requirements more effectively than LA-ACB. In other words, the hybrid access method achieves a lower delay (76.72 ms at 4000 requests) compared to ACB and LA-ACB, ensuring QoS for time-sensitive applications.

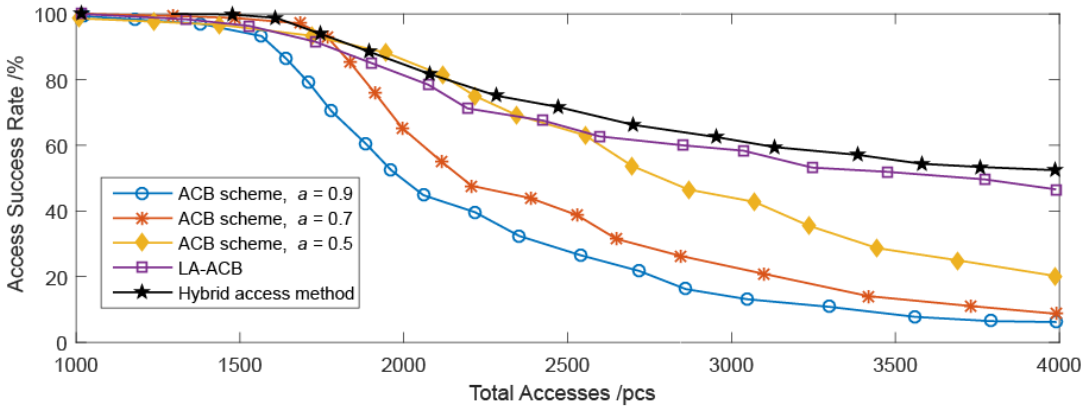

Figure 12: Comparison of access success rates for concurrent services in the uniform model, with the hybrid method outperforming ACB and LA-ACB by reducing collisions and improving resource use

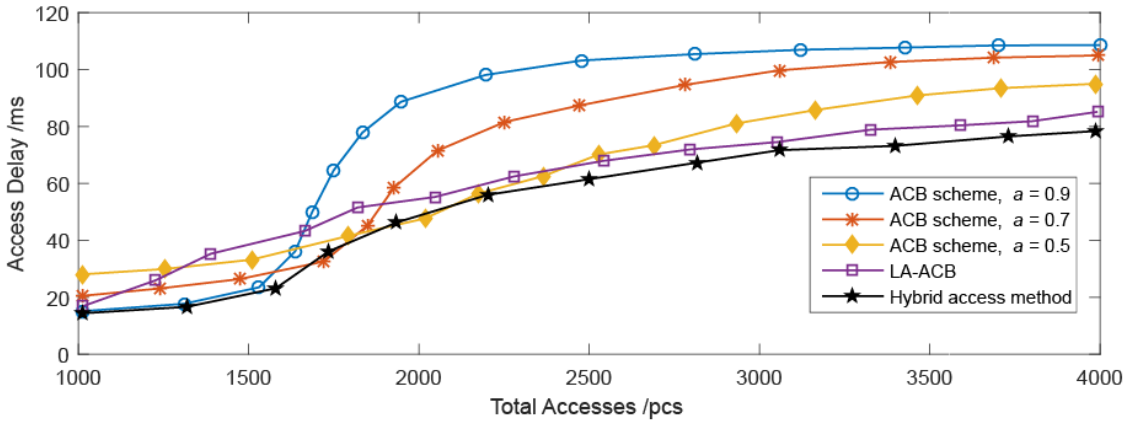

Figure 13: Comparison of average access delays for concurrent services in the uniform model, showing the hybrid method's lower delays (76.72 ms), ensuring timely transmission

The comparison of access success rates for multiple types of concurrent services is illustrated in Fig. 12, while Figure 13 shows the comparison of average access delay for these concurrent services. The hybrid access method outperforms ACB and LA-ACB, showing a higher success rate and lower delay, especially when the number of access applications reaches 4000. At this point, the hybrid method achieves a 52.43% success rate and an average delay of 76.72 ms, demonstrating undeniable advantages in efficiency and effectiveness.

These results indicate that the hybrid access method, especially under a uniform distribution model, significantly improves the system's access success rate and average access delay, thereby meeting the QoS (Quality of Service) needs for high-priority services in large-scale IoT terminal access scenarios.

4.2.2 Simulation results and analysis of beta distributed access model

When the beta distribution model is adopted, the performance of the hybrid access method is evaluated in terms of the access success rate and average access delay for high-priority services.

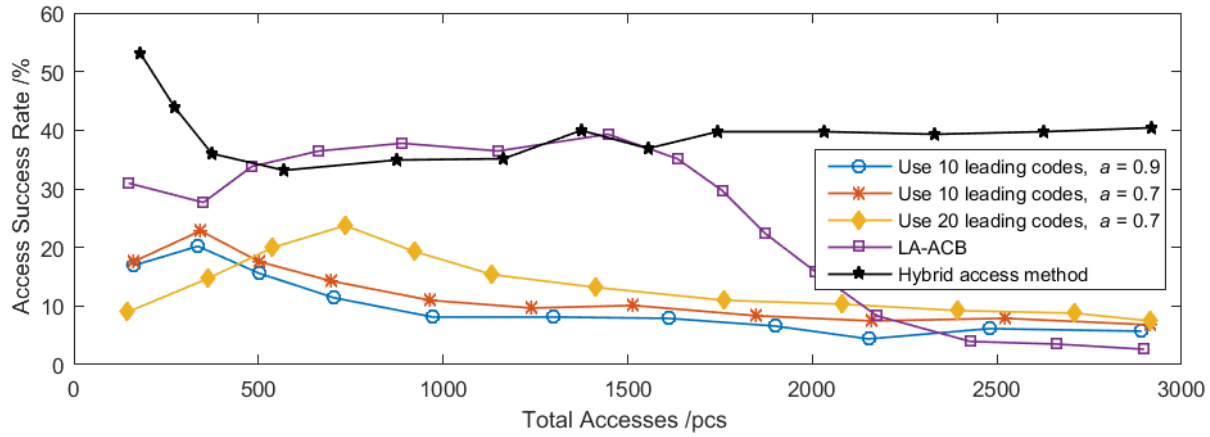

Figure 14: Comparison of access success rates for high-priority services in the beta distribution model, with the hybrid method excelling (42.07% at 4000 applications) through dynamic adjustments and efficient resource use

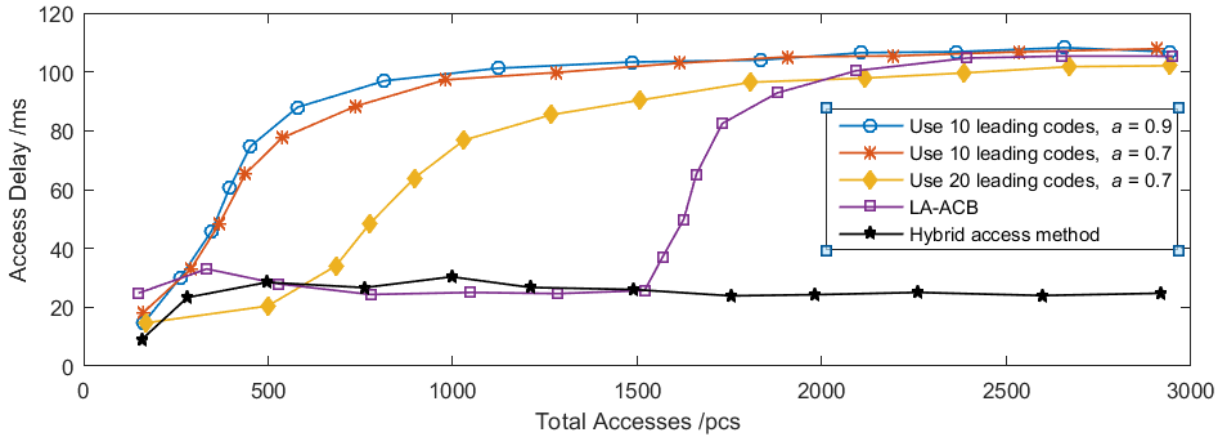

Figure 15: Average access delays for high-priority services in the beta distribution model, with the hybrid method achieving a lower delay (82.02 ms at 4000 applications) than ACB and LA-ACB

Fig. 14 illustrates the access success rate of high-priority services under the beta distribution model. The results indicate that the hybrid access method achieves a higher access success rate compared to the ACB and LA-ACB methods. This improvement is due to the dynamic adjustment of access application amounts and access parameters in the next timeslot, which optimizes the allocation of resources for high-priority services.

Fig. 15 presents the comparison of average access delay for high-priority services using the beta distribution model. The hybrid access method demonstrates a lower average access delay compared to ACB and LA-ACB methods. This reduction in delay is attributed to the method's ability to better predict and manage access requests, thereby minimizing the waiting time and improving overall efficiency.

These results highlight the advantages of the hybrid access method in managing high-priority service requests, ensuring higher access success rates, and reducing average access delays under the beta distribution model. This demonstrates the method's effectiveness in handling dynamic and bursty traffic patterns in large-scale IoT environments.

The total number of system preamble codes is 60. When high-priority services are concurrent with low-priority services, the access success rate is shown in Fig. 16, and the average access delay is shown in Fig. 17.

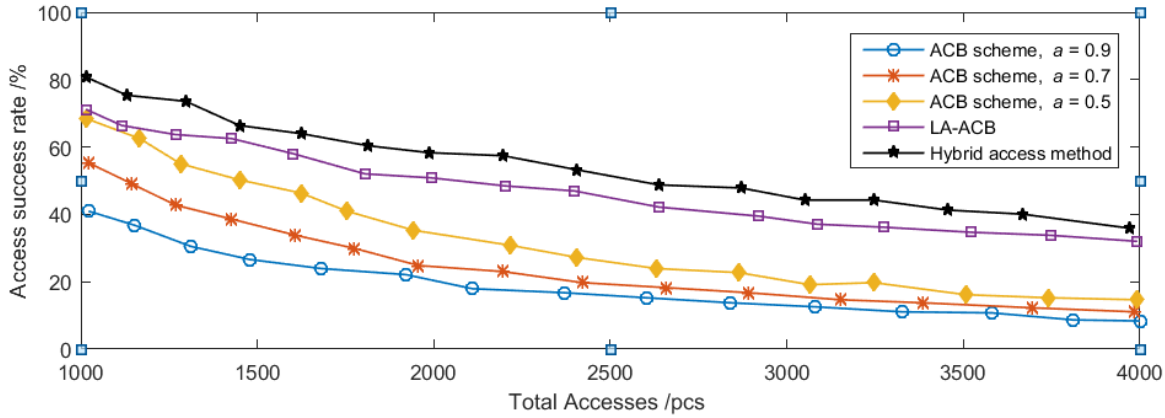

Figure 16: Access success rate for concurrent services in the beta distribution model, with the hybrid method achieving 42.07% at 4000 applications, surpassing ACB and LA-ACB

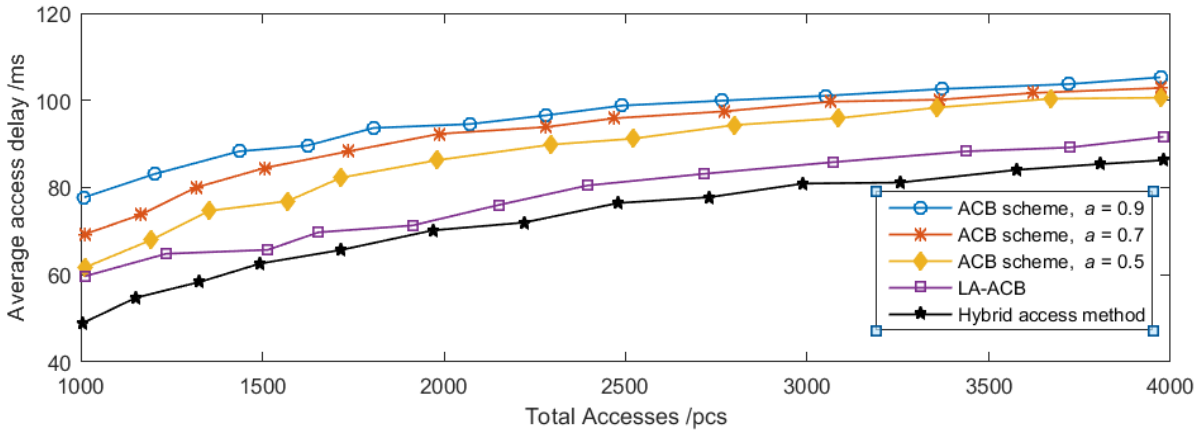

Figure 17: Average access delay for concurrent services in the beta distribution model, with the hybrid method achieving 82.02 ms, outperforming ACB and LA-ACB

Figure 16 shows access success rate for concurrent services under the beta distribution model. The hybrid access method outperforms ACB and LA-ACB methods, achieving a success rate of 42.07% at 4000 applications, demonstrating robust handling of burst traffic. Figure 17 illustrates average access delay for concurrent services under the beta distribution model. The hybrid access method reduces delay to 82.02 ms at 4000 applications, ensuring better performance for high-priority and time-sensitive services. In fact, it is these very measures of performance that represent important favorable points for the proposed hybrid model over conventional algorithms like ACB and LA-ACB.

The experimental results also reveal that the access success rate and average access delay are significantly improved by the proposed hybrid access method. In addition, it well satisfies the requirements brought by the Quality of Service of high-priority traffic for periodic and bursty large-scale terminal access requests. It enables the method to predict the volume of the access application effectively in the next timeslot in a dynamic way by taking advantage of the historical state of the preamble code, without assuming anything about the quantity of access applications.

The predictability allows for the tailoring of the hybrid access method to the various characterizations of different services, hence optimality in the choice of access methodologies. This leads to a substantial increase in system throughput that ensures reliable and efficient communications over large-scale IoT topologies.

In summary, the hybrid access method enhances the performance of the system and also responds to robustness and scalability challenges; hence, it is the best against all the complexities in communications in IoT at a metro railway station. Dynamic adaptability and predictive accuracy make this tool indispensable to maintain the optimum service level and meet the stringently demanding QoS of critical infrastructure.

5 Discussion

The proposed hybrid access scheme constitutes one of the key improvements in congestion management schemes over large-scale IoT networks, especially in highly populated areas such as in metro stations. In the process, SA-ACB merging is targeted at the solution of fundamental issues like low access success rates and high delays in a network. Higher performance indices are promised to be exhibited compared with the existing methodologies LA-ACB and traditional ACB. For instance, under the uniform distribution model, the maximum access success rate reaches 52.43% at 4000 requests, which is far beyond the limitation of LA-ACB owing to the inefficiency of resource utilization when

requests are too many. Besides, this approach ensures an average latency of no more than 76.72 ms for high-priority services that strictly meet the QoS requirement. Under correspondence, within the beta distribution model, robustness exposed to bursty traffic by the hybrid approach achieved 42.07% in success rate and 82.02 milliseconds average delay.

Those advantages come forth due to novelty in resource allocation and predictive adjustments that this hybrid method will implement. The method dynamically adapts the ACB control parameters in view of historical data and real-time estimation to optimize channel utilization with minimum collision. It efficiently spreads the network load in a dual-access approach wherein small data services are managed by SA and large delay-sensitive services are overseen by ACB. This flexibility is a key ingredient for achieving high scalability and reliability, especially under scenarios that exhibit diversified traffic patterns where high-priority applications must coexist with low-priority ones.

The practical implications of these findings are huge. Hybrid should guarantee environments like metro stations with very low latency and high access success ratios, dependably surveilling the very important equipment of elevators and escalators, while improving operational safety and efficiency. Besides, this solution also provides a scalable and economically feasible way to handle congestion in IoT networks, thus making it suitable for smart city, industrial automation, and, generally speaking, high-traffic IoT systems. Future works may further optimize the proposed approach for energy efficiency and extend its applicability to realistic traffic for further generalization. These results have established the hybrid access method as a robust and practical solution to handle congestion in large-scale IoT networks.

6 Conclusion

The paper proposed an IoT-based congestion management strategy for mass data access from the elevator terminals at the metro station. This method categorized the business data by volume and latency requirements and adopted SA for delay-tolerant services and ACB for real-time services. Besides, in the proposed methodology, dynamically adjusting ACB control parameters was adopted to optimize the access efficiency for terminals. The effectiveness of the approach is corroborated by the simulation results: from a uniform distribution model, based on 4000 access requests, the hybrid method can achieve an access success rate of 52.43% and an average access delay of 76.72 ms. From the Beta distribution model, 42.07% with an average access delay of 82.02 ms can be achieved. It is presented that the Hybrid Access Method increases the access success rate greatly and decreases the delay hence fulfilling the QoS requirements for high-priority services in a large-scale IoT environment. Future investigations ought to encompass practical implementation and examine more extensive traffic models, sophisticated prediction methodologies, and scalability to further substantiate and augment the applicability and dependability of the method. Nevertheless, the suggested congestion control approach, primarily corroborated through simulations, may not entirely reflect the intricacies of real-world scenarios and the diverse traffic patterns encountered. Therefore, even the refined uniform and Beta distribution models need further refinement and validation in order to ensure their accuracy against different scenarios. The scalability of the method, especially above 4000 access requests, was not deeply analyzed, as was the application of the method to other IoT applications. It has to be implemented on-site, considering variations in traffic models, advance prediction methods using machine learning techniques, and scalability analysis for performance evaluation. Extension of the method to other IoT applications, investigation of energy efficiency, and incorporating robust security will ensure its sustainability, hence reliable in different IoT environments.

Acknowledgment

Thanks to our families and colleagues who supported us morally.

Funding statement

Not applicable

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Authorship contribution statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

Availability of data and materials

On Request

Declarations

Not applicable

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CM-OOA：An Energy-Efficient Clustering Algorithm for Wireless Sensor Networks Using Chaotic Mapping and Osprey Optimization

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Keywords: emergency communication system, wireless sensor network, prey optimization, chaotic mapping, energy consumption

Received: December 17,2024

A wireless sensor network (WSN) represents a promising approach for establishing self-organizing wireless networks comprising a substantial number of wireless sensors, with the objective of facilitating communication in regions where the existing communication infrastructure has been severely disrupted. In order to address the issue of excessive energy consumption by cluster heads and central nodes in emergency communication networks of wireless sensor networks, this paper proposes an emergency communication algorithm for wireless sensor networks based on chaos mapping and osprey optimization. Firstly, an optimization algorithm based on chaos theory is used to select the virtual position of the initial population of the Osprey optimization algorithm. This is achieved by simulating the randomness and unpredictability of chaotic systems. Secondly, the osprey optimization algorithm and the improved fitness function are used to select the optimal cluster head combination. In the selection process, six factors, such as the energy level of network nodes, the distance between cluster heads, the distance between cluster heads and base stations, the distance between cluster heads and ordinary nodes, the variance of the distance between cluster heads and base stations and the variance of the distance between cluster heads, are comprehensively considered. Finally, the heuristic function of FA-star algorithm is used to select the next hop node to transmit the message. The results of the simulation demonstrate that the residual energy of the CM-OOA algorithm is 14% higher than that of the CGWOA algorithm following the transmission of 1000 data rounds. This figure is 54% higher than that observed for the PSO-C algorithm. The findings demonstrate that the CM-OOA algorithm effectively extends the network lifetime and preserves a favorable load balance in diverse network settings.

Povzetek: CM-OOA algoritem s kaotičnim preslikovanjem in optimizacijo osprejev natančno izbere optimalna vozlišča, zmanjšuje energijsko porabo in podaljšuje življenjsko dobo WSN, kar je ključnega pomena za nujne komunikacijske sisteme.

1 Introduction

In recent years, with the gradual warming of the global climate, after earthquakes, floods, strong tropical storms or other disasters, fixed communication network facilities may be completely destroyed or most of them may not work normally. Communication is extremely important for emergency rescue and disaster relief [1]. At this time, we need an emergency network that can be quickly deployed without relying on any fixed network facilities.

A wireless sensor network is a network composed of a large number of randomly distributed nodes that are capable of self-organization. The primary function of the system is to monitor and obtain data from the target area and subsequently transmit it to the base station. A plethora of potential applications can be envisaged in the context of the Internet of Things, including those in the military, aerospace, ocean and agricultural sectors, among others. Due to its low cost and ease of use, it is capable of functioning in a multitude of challenging environments. In areas inaccessible to humans, unmanned aerial vehicles (UAVs) can be deployed to establish wireless communication networks [2]. It can be reasonably proposed that wireless sensor networks represent a potential method for emergency communication. However, the considerable number of sensor nodes, coupled with the limited energy capacity and relatively short operational lifespan, present significant challenges. Nevertheless, the length of time that emergency communication networks based on wireless sensors can remain operational is a significant challenge. One promising avenue for further research is to enhance the energy efficiency of these networks, thereby prolonging their operational lifespan.

Aiming at the energy consumption problem of WSNs in data transmission, it is an effective method to prolong the

life of wireless sensor networks by selecting cluster heads for network nodes and data fusion [3]. At present, cluster head selection algorithm usually uses two technologies, one is to randomly select cluster heads through thresholds, and the other is to design appropriate fitness function to select cluster heads by using swarm intelligence technology. Some scholars have also proposed to solve the problem of rapid death of central nodes by using non-uniform clustering algorithm.

Firstly, scholar Wendi Rabiner Heinzelman proposed LEACH protocol, which randomly rotates cluster heads with a certain threshold, and reduces energy consumption and prolongs network life cycle by clustering nodes to cluster heads [4]. Saxena Madhvi scholars enhanced the original LEACH protocol by introducing new algorithms CHME-LEACH and CHP-LEACH, reducing communication energy consumption and prolonging network life [5]. Jonnalagadda Suman scholars put forward an energy-aware routing protocol MAX LEACH, which is suitable for heterogeneous networks and homogeneous networks, to minimize the energy consumption of nodes and extend the network life [6]. These scholars employ data fusion techniques with the objective of reducing network energy consumption and extending network lifetime.

Secondly, with the continuous development of intelligent algorithms, intelligent algorithms have broad application prospects in selecting cluster heads in wireless sensor networks. The selection of cluster heads in wireless sensor networks is very similar to swarm intelligence algorithm. Therefore, Gülbaş, Gülşah scholars introduced simulated annealing algorithm to propose LEACH-SA algorithm, and introduced simulated annealing algorithm to select cluster heads to extend the network life [7]. Mishra Rashmi scholars select the optimal number of cluster heads among dense network nodes by introducing butterfly optimization algorithm, and select the next hop node by introducing ant colony optimization algorithm in the data transmission stage [8]. Nurul muazzah abdul latiff scholar proposed PSO-C protocol by introducing particle swarm optimization algorithm, which reduced network energy consumption and extended network life [9]. Bejjam Komuraiah scholar put forward at the 14th International Conference on Computing Communication and Networking Technologies in 2023 that genetic algorithm is introduced into wireless sensor networks, which makes the network balance load and optimize, and increases the better results in lower cycle [10]. Muntather Almusawi scholars proposed the CGWOA protocol by introducing chaos algorithm and grey wolf optimization algorithm, which reduced energy consumption by reducing the transmission distance of network nodes [11]. The application of cluster intelligence algorithms enables the selection of cluster heads that optimize the energy consumption of the network, thereby extending its operational lifespan.

Thirdly, for heterogeneous networks, there are also many scholars' research on heterogeneous clustering algorithm. Verma Axel and other scholars put forward the ECSSEEC protocol based on enhanced cost and sub-era. In ECSSEEC protocol, the optimal number of clusters is selected by modeling the cost function, and the previously selected cluster heads are rotated again as normal sensing nodes in the future rounds of the sub-cycle [12]. Das Rahul proposed a large-scale energy-aware trust optimization algorithm for cluster head selection and malicious node detection. The harmonic search genetic algorithm was originally used to select cluster heads according to energy, trust, distance and density. By considering the trust value, this method avoids choosing malicious nodes as cluster heads, and then uses energy-aware trust estimation models within and between clusters to detect malicious nodes, this depends on two modules: direct trust and indirect trust between clusters and within clusters [13]. Pal. Raju proposed a multi-objective binary grey wolf optimizer to find the clustering method in heterogeneous networks, and extended the network life cycle through five objectives: maximizing the overall cluster head energy, minimizing the cluster head compactness, minimizing the number of cluster heads, minimizing the energy consumption from non-cluster heads to clusters, and maximizing the cluster spacing [14]. These scholars have developed heterogeneous wireless sensor networks with different energy nodes. One method of prolonging the network life cycle is to increase the energy available to the cluster head nodes. The comparison between algorithms is shown in Table 1.

Table 1: Comparison of the different types of protocols involved.

Mode	References	Vantage	Drawbacks
Threshold protocol	LEACH.2000[4]	The algorithm is simple, and the cluster head is selected by the threshold.	Cluster heads are selected by threshold, and random selection can lead to irrational combinations of cluster heads.
	CHP-LEACH.2024 [5]		
	MAX LEACH.2023[6]		
Machine learning protocol	LEACH-SA.2023[7]	Through the continuous selection of swarm intelligence, until the reasonable cluster head selection.	Cluster intelligence is used to select the cluster head and the cluster head nodes should be reasonably located. Better reduction of energy consumption.
	Mishra Rashmi.2023[8]		
	PSO-C.2007[9]		
	CGWOA.2024[11]		
Non-uniform protocol	ECSSEEC.2023[12]	The number of nodes within the cluster is not the same, which can avoid the rapid death of the central node.	Clusters with inconsistent number of nodes in the cluster may lead to a large energy consumption gap between clusters.
	Das Rahul.2024[13]		
	Pal. Raju.2024[14]		

The various clustering routing algorithms proposed by the aforementioned scholars have the potential to reduce the energy consumption of wireless sensor networks and to extend their operational lifetime. However, there is a lack of reasonable allocation methods for the election of cluster heads and the selection of path nodes from cluster heads to base stations in the process of algorithm design. In this paper, a chaos mapping Osprey optimization algorithm (CM-OOA) is proposed to reduce network energy consumption, improve clustering efficiency and prolong network life. Firstly, the randomness and ergodicity of chaotic mapping algorithm are used to

search for the global optimal solution. The core of chaotic mapping algorithm is chaotic mapping, which is a discrete nonlinear dynamic system that can produce seemingly random state changes. Chaos mapping algorithm can effectively search in the solution space, so as to find the optimal solution or near optimal solution of the problem. Secondly, by using the Osprey optimization algorithm, the characteristics of local and global optimization can be well balanced. Find out all the optimal solutions or approximate optimal solutions to find the most suitable node as the cluster head, so that each cluster head node has the highest energy, the shortest distance to the base station, the shortest distance from the node to the cluster head and the more balanced distance between cluster heads. Finally, by comparing the distance from the node to the base station with the distance from the cluster head to the base station, and the energy of the cluster head itself, the common node selects the cluster head node and performs the cluster operation. The node to base station Euclidean distance is less than the cluster head node to base station Euclidean distance and will be transmitted directly to the base station. In the inter-cluster routing stage, based on the FA-star heuristic search algorithm, the heuristic function of four factors, namely the distance from the starting node to the forwarding node, the distance from the forwarding node to the base station, the energy of the node and the forwarding times of the node, is optimized. Select the most suitable next-hop routing node from the neighbor nodes composed of all nodes that meet the conditions. For the hot spot phenomenon that may occur in wireless sensor networks, because some nodes directly transmit to the base station, and the inter-cluster forwarding nodes include cluster head nodes and ordinary nodes, the energy consumption is more balanced, which will not cause the nodes to die too quickly, thus prolonging the communication time of the emergency communication network.

2 System model

2.1 Communication network structure model

The topology model of wireless sensor network adopted in this paper is shown in Figure 1. The simulation model assumes that N nodes are randomly distributed in a square area of M*M and all nodes are wireless sensors of the same type. The network model is shown in Figure 2. In order to accurately calculate the information of the node and ensure that the base station receives and sends data continuously and stably, the node can independently select the appropriate transmission power according to the energy consumption model [15-16]. In order to avoid the influence of bad weather and human factors, network nodes need to meet the following requirements:

1) The random dropping area M×M contains N sensor nodes, and the node positions after dropping are fixed.

2) Sensor nodes have unique and different ids.

3) The base station has unlimited energy and no signal interference in the area.

4) The power sent and received by each sensor node is controllable.

5) All sensors have the same properties and their positions remain unchanged relative to the base station.

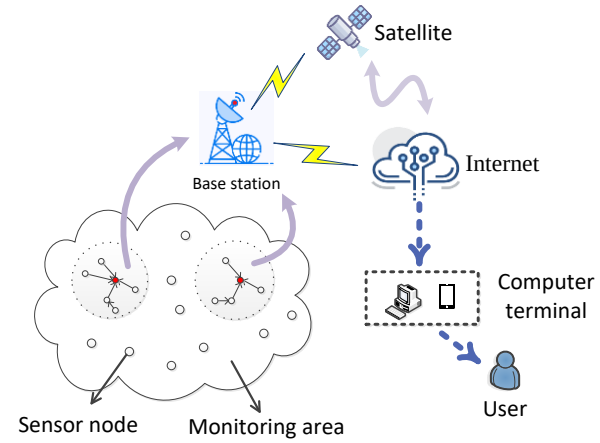

Figure 1: Network topology model.

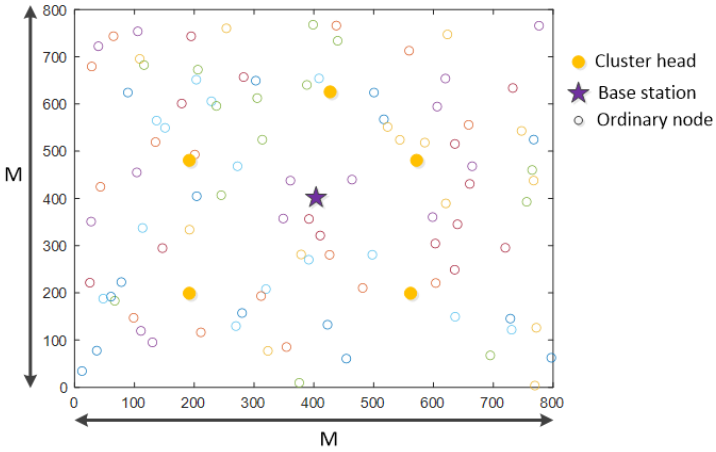

Figure 2: Emergency communication network mode.

There are three main communication modes in the emergency communication network. Firstly, Communication within a cluster. Because information transmission is only between clusters, this method consumes less energy for wireless sensor networks [17]. Secondly, Communication of the same cluster head node. When users are not in the same cluster head node, if communication is needed, the common node will report to the superior cluster head node and communicate with each other through the cluster head node. Thirdly, Communication between different cluster head nodes. When users are neither the same cluster nor the same cluster head node, if communication is needed, ordinary nodes will report to their superior's step by step and contact each other through base stations [18].

In the communication process of wireless sensor network, the third process needs the information transmission of the whole wireless sensor network. User information is transmitted in both directions from ordinary nodes to base stations and then to ordinary nodes, so energy consumption is mainly concentrated in the third mode

[19]. Therefore, this paper mainly studies the energy consumption of the third communication mode.

2.2 Communication energy consumption model

In this paper, the wireless sensor emergency communication network adopts the first-order wireless communication energy consumption model [20], which can be divided into short-distance free space model and long-distance multi-path model according to the transmission distance. The specific formulas are as follows: (1) - (3).

$$E_{Tx}(K,L)=\begin{cases}K*E_{elec}+K*\varepsilon_{fs}*L^2, L<D_0\\ K*E_{elec}+K*\varepsilon_{mp*}L^4, L\geq D_0\end{cases} \quad (1)$$

$$D_0=\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

$$E_{Rx}(K,L)=K*E_{elec} \quad (3)$$

In formulas (1) - (3), E_{Tx} is the energy consumption for sending K bit data; E_{elec} represents the energy consumption associated with the transmission and reception of a single bit of data; ε_{fs} is the loss factor of free space model; ε_{mp} is the energy loss factor of multipath attenuation model; L is the data transmission distance; E_{Rx} is the energy consumption for receiving K bit data.

3 Research on energy consumption of three-layer network

From the network topology diagram, we can see that the data acquisition and transmission stage of wireless sensor networks can be divided into three levels: ordinary node layer, cluster head node layer and base station layer, as shown in the Figure 3.

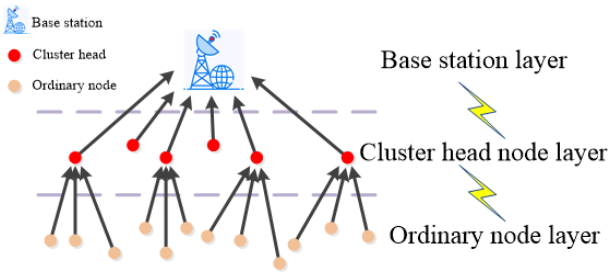

Figure 3: Three-layer network model.

Through the formulas (1) -(3) in the network energy consumption model, the main reasons of energy consumption in the three-layer network can be analyzed respectively. The data transmission of ordinary nodes is the key to energy consumption. When the transmission distance exceeds D_0, the energy consumption during data transmission will increase sharply, so the appropriate location of cluster head nodes is very important. Attention should also be paid to the direction of data transmission in the process of ordinary nodes entering the cluster, but the "hot spot effect" around the base station in wireless sensor networks is also the key to extend the network life [21]. Through formula (1), it can be seen that multi-hop transmission is better than single-hop transmission in long-distance transmission. However, in multi-hop transmission, in the process of selecting the next hop node from the cluster head node to the base station, the same next hop node will be selected continuously, resulting in the rapid death of the node. To solve these problems, it contains three main problems:

1) Does the cluster head combination affect the network energy consumption?
2) How to plan the direction of data transmission to solve the problem of “hotspot effect” where the center node dies quickly?
3) Can the multi-hop cluster head node choose the same node as the forwarding node every round?

In the past, many researchers did not comprehensively consider the above problems from the perspective of three-tier network energy consumption model. Some researchers randomly select cluster head combinations, which leads to the irrationality of cluster heads, and then leads to redundant energy consumption. Because the ultimate goal of data is the base station, the data transmission direction can only be close to the base station. However, most researchers do not consider the influence of the clustering operation process of ordinary nodes on the data transmission direction, and all nodes are clustered. This process causes some nodes to transmit data in the opposite direction to the base station, resulting in energy transmitted in the opposite direction. Some researchers also use multi-hop in long-distance transmission, but the forwarding times of the next hop node are not considered, which can not be ignored for the node life.

Aiming at the above three problems, this section will analyze the energy consumption reasons of each layer network from the perspective of three-layer network energy consumption, and put forward a reasonable cluster head selection, data transmission direction planning, and next-hop node selection and processing algorithm in multi-hop mode.

3.1 Reasonable cluster head combination

In the process of selecting cluster head nodes by ordinary nodes, the distances from different cluster head node combinations to nodes are different. Therefore, it has an impact on the overall energy consumption of the network. From the energy transmission formula (1), it can be seen that the distance is directly proportional to the energy consumption. Reasonable cluster head combination can better reduce the energy consumption of sending data due to distance.

In the osprey optimization algorithm (OOA), the optimal position of individual osprey is obtained by updating the position of individual osprey and comparing the fitting

function values of each individual position. However, the osprey optimization algorithm is limited by its slow convergence speed and tendency to converge to the local optimal solution. Aiming at the problems of slow convergence speed and easy to fall into local optimal solution in cluster head combination selection, this algorithm combines population initialization process with K-means++ algorithm and chaotic algorithm to form chaotic osprey optimization algorithm (CM-OOA). The output of chaotic Osprey optimization algorithm is similar to the selection of cluster head combination in wireless sensor networks. As shown in Table 2, there is significant consistency between the characteristics of wireless sensor networks and the principle of chaotic Osprey optimization algorithm.

Table 2: Similarity correspondence table between wireless sensor networks and chaotic mapping osprey optimization algorithm.

WSN	CM-OOA
Sensor node number	Dimension position size
Node group	Individual position of osprey
Cluster head node combination	Optimal individual position of osprey
Combination of all pre-selected cluster head nodes	All positions of osprey population

Good population initialization allows the CM-OOA algorithm to start searching from several different initial starting points, which helps the algorithm to explore multiple regions of the solution space, thus increasing the likelihood of finding a globally optimal solution. If the individuals in the initial population are too concentrated, the algorithm may quickly converge to the local optimal solution and ignore other potentially better solutions. A diverse initial population helps to avoid this. Proper population initialization allows the algorithm to find better solutions at an early stage, thus speeding up the convergence of the whole search process. Therefore, the algorithm in this paper performs the population initialization operation in two ways.

3.1.1 Kmeans++ algorithm for clustering

Initializing the populations is an important step in the CM-OOA algorithm, which uses the Kmeans ++ clustering algorithm for clustering to obtain a more accurate optimal solution. The initial population nodes are selected by the centre position of each cluster group. The calculation of the cluster centre position is based on the application of equations (4) and (5). The effect of the clustering algorithm is shown in Figure 4.

$$X_m = \sum_{i=0}^{t} X/t \quad (4)$$

$$Y_m = \sum_{i=0}^{t} Y/t \quad (5)$$

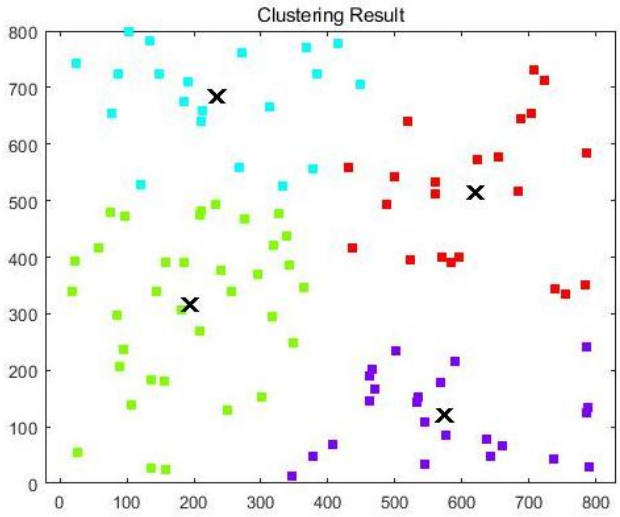

Figure 4: Clustering algorithm effect.

3.1.2 Chaos mapping optimization

Initializing the population by Logistic chaotic mapping can enhance the global search ability and help CM-OOA algorithm jump out of the local optimal solution [22]. The randomness and unpredictability of Logistic chaotic mapping can prevent the algorithm from converging to the local optimal solution prematurely. Logistic chaotic mapping can adapt to different search spaces and optimization problems, and has good universality. Therefore, Logistic chaotic mapping can be easily combined with Osprey optimization algorithm to form CM-OOA algorithm, so as to make better use of their respective advantages to deal with the problem. Logistic chaotic mapping formula is as follows:

$$P_{i+1} = \alpha * P_i * (1 - P_i) \quad (6)$$

In the formula, α is the control parameter, and the value is taken in (0,4]. Pi is the transformation of the coordinates of the initial population into polar angles as an initial value.

The detailed process of CM-OOA algorithm:

Step 1. Population initialization.

The virtual initialization of the Osprey cluster is achieved by means of the circular symmetric chaotic mapping algorithm and the K means++ clustering algorithm.

Step 2. Initialization of osprey population based on location mapping algorithm.

The virtual position of the initialized osprey population is obtained, and the real node number in the wireless sensor network is mapped by the Euclidean distance d from the node to the virtual position and the energy e of the node itself. The osprey population is initialized to P(t) = {Pt_1, Pt_2, Pt_3…}, and the individual Pt_i position of osprey is Pt_i = {X_{i1}, X_{i2}, X_{i3}…}.

Step 3. Calculate the fitness function.

Fi=fitness ($P_{i(t)}$) is the fitness value of individual $P_{i(t)}$ of osprey at time t, which is used to evaluate the strength of solving energy consumption problems at the position of osprey.

Step 4. Osprey individuals look for schools of fish.

Through the comparison of fitness values, the individual positions of osprey whose fitness values are smaller than their own are combined as fish schools, Fish = $\{P_{k(t)}|k\in \{1, 2,\ldots N\} \wedge F_k<F_i\} \cup \{P_{best}\}$.

Step 5. Individual fishing of osprey.

In Step 3, the osprey individual P looks for his own Fish school. If the Fish school fish is empty, it is considered that the osprey individual X has successfully caught the target fish and directly goes to Step 5 for the osprey individual to eat fish. Otherwise, the osprey individual P randomly selects a target Fish in the fish school fish for fishing operation. Because the node coordinates are two-dimensional, the coordinates X and Y are calculated separately for fishing operation. The formula of specific fishing process is as follows:

$$P_{t,jx}^{Fish} = P_{t,jx} + R_{t,j} * \left(P_{Fishx} - I_{t,j} * P_{t,jx}\right) \quad (7)$$

$$P_{t,jy}^{Fish} = P_{t,jy} + R_{t,j} * \left(P_{Fishy} - I_{t,j} * P_{t,jy}\right) \quad (8)$$

In formulas (7) - (8), $R_{t,j}$ is a number randomly generated between [0,1]; $I_{t,j}$ is randomly selected between 1 and 2; $P_{t,jx}$ is the X coordinate position of osprey individual P in the J-th dimension of the T-th round; P_{Fishx} is the x coordinate position of the target fish x of the osprey individual p; $P_{t,jy}$ is the Y coordinate position of osprey individual P in the J-th dimension of the T-th round; P_{Fishy} is the y coordinate position of the target fish x of the osprey individual p.

Step 6. Osprey individuals eat fish.

In Step 4, the position of individual P of osprey changes. First, the process Step 2 Location Mapping maps the position of the individual osprey to the network node number [23]. Secondly, the fitness value before and after the change of osprey individual is judged to judge whether the osprey individual catches the target fish. Finally, if the fitness value is greater than that before the change, the osprey individual P fails to catch the target fish successfully, and the process is directly carried out in Step 6. Otherwise, the osprey individual P successfully catches the target fish and eats the fish. Because the node coordinates are two-dimensional, the coordinates x and y are calculated separately for fish eating operation. The specific formula for eating fish is as follows：

$$P_{t,jx}^{Fish} = P_{t,jx} + \left(lb_t + R_{t,j} * (ub_t - lb_t)\right)/t \quad (9)$$

$$P_{t,jy}^{Fish} = P_{t,jy} + \left(lb_t + R_{t,j} * (ub_t - lb_t)\right)/t \quad (10)$$

In formulas (9) - (10), $R_{t,j}$ is a number randomly generated between [0,1]; ub_t is the upper boundary of the dimension coordinate; lb_t is the lower boundary of the dimension coordinate; $P_{t,jx}$ is the X coordinate position of osprey individual P in the J-th dimension of the T-th round; $P_{t,jy}$ is the Y coordinate position of osprey individual P in the J-th dimension of the T-th round; T is the number of rounds of population iteration.

Step 7. New osprey population position.

P(t+1) = {...} indicates a new generation of osprey population generated by individual osprey searching for fish, individual osprey catching target fish and individual osprey eating fish [24].

Step 8. Algorithm termination condition.

The algorithm repeats the operations from Step 3 to Step 7 until the maximum number of iterations is reached.

Step 9. Algorithm output.

The optimal individual fitness value and osprey position are obtained, that is, the optimal cluster head combination.

Step 10. Ordinary nodes into the cluster operation.

By calculating the fitness function of clustering and comparing and selecting, ordinary nodes select the optimal clustering node for clustering operation.

Step 11. Data transfer operation.

The initial node selects the jump node through heuristic search FA-star algorithm for data transmission.

Firstly, CM-OOA algorithm iteratively updates the individual position of the osprey population, compares the individual position fitness values and selects the smallest individual fitness value, that is, the optimal individual position of the osprey. Secondly, ordinary nodes enter the cluster by calculating the fitness value of the cluster head. Finally, the improved FA-star algorithm is used for inter-cluster routing transmission. The detailed flow of CM-OOA algorithm is shown in Figure 5.

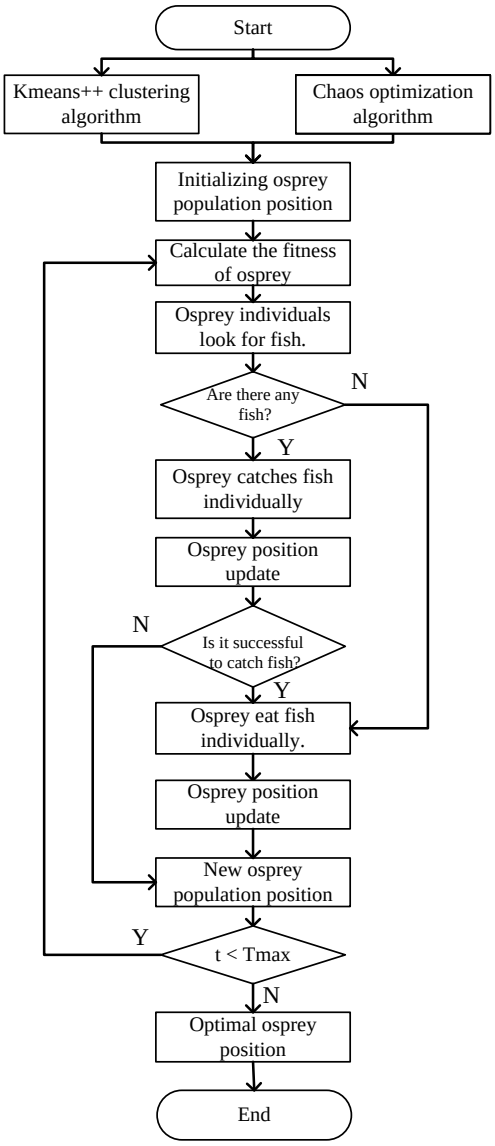

Figure 5: Flow chart of selecting cluster head by CM-OOA algorithm.

3.2 Planning of data transmission direction

In wireless sensor networks, all nodes are clustered, so when the nodes are close to the base station, they will still be clustered. As shown in Figure 6, it causes the problem that the node data is transmitted outward first and then inward. From the energy consumption model, it can be calculated that the energy consumption of all nodes in data clustering is E_2, while the energy consumption of nodes in direct transmission is E_1. From formulas (11) - (12), it can be concluded that the direct transmission mode of some nodes has low energy consumption.

$$E_1 = K * E_{elec} + K * \varepsilon_{fs} * {L_1}^2 \quad (11)$$

$$E_2 = 2 * K * E_{elec} + K * \varepsilon_{fs} * (L_2^2 + L_3^2) \quad (12)$$

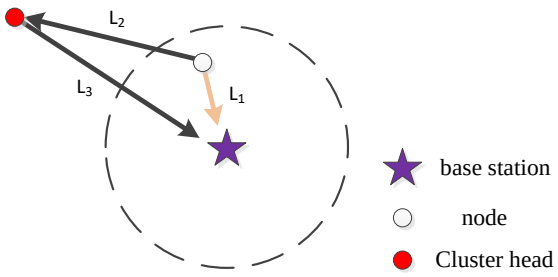

Figure 6: Data flow direction comparison chart.

In order to solve the problem of data transmission direction, the algorithm is based on the mathematical midline theorem. As shown in Figure 7, when the common node is located in the midline of the link from the cluster head node to the base station, the distances from the common node to the cluster head and the base station are equal [25]. Therefore, when $d_3 > d_1$, the common node will perform the cluster head selection operation.CM-OOA algorithm reduces energy consumption by preventing nodes from transmitting far away from the base station. As shown in Figure 8, the cluster head node CH_2 will be selected first when the distance d3 from the common node to the base station is greater than the distance d_2 from the cluster head node CH_2 to the base station. Although it can be seen from the figure that the distance d4 from the common node to the cluster head node CH_1 is smaller than the distance d_5 from the cluster head node CH_2, the cluster head node $\{CH_2\ldots\}$ of the common node will be pre-selected with less energy. If the pre-selected cluster head set is empty, data is directly transmitted to the base station.

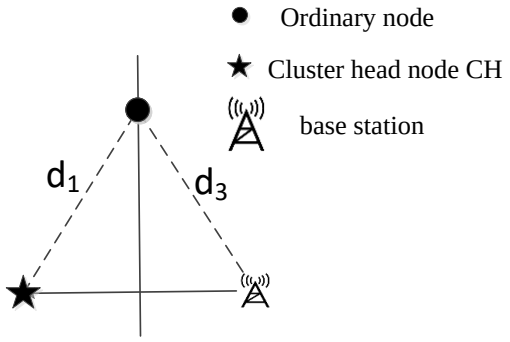

Figure 7: Median line

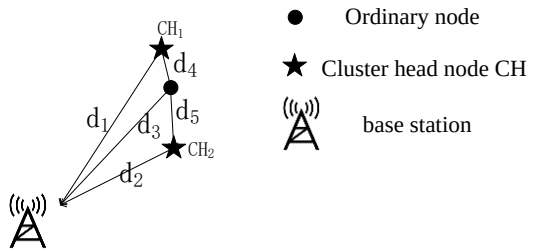

Figure 8: Cluster head selection model of common nodes.

3.3 Best next hop node

According to the energy consumption model, transmission energy consumption is directly proportional to the square of distance, and data transmission is the main energy consumption of wireless sensor networks. According to the geometric cosine theorem and the first-order radio network energy model [26]. Therefore, the algorithm in this paper adopts multi-hop mode for data transmission.

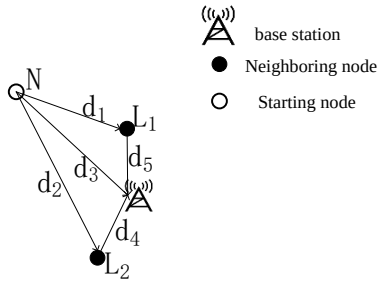

Figure 9: Neighbor node selection model.

In the process of multi-hop data transmission, FA-star algorithm and heuristic search are used to select the transmission path. The destination base station is reached by finding the minimum cost of the path [27]. In this algorithm, the neighbor nodes are selected in the same way as the cluster heads in the clustering algorithm. The Euclidean distance d_1 from the start node N to the neighboring node is less than the Euclidean distance d_3 from the start node to the base station, so the neighboring node chooses L_1. As shown in Figure 9, the starting node n of the neighboring node $\{L_1...\}$ directly transmits if the neighboring node is empty.

4 Design of CM-OOA algorithm

In this paper, the energy consumption of three-layer network is analyzed in detail, and the clustering algorithm of CM-OOA network is proposed by combining the chaotic Osprey optimization cluster head combination selection algorithm with the data transmission direction and the best next hop strategy. The algorithm is divided into cluster head selection stage, cluster establishment stage and data transmission stage. The algorithm flow chart is shown in the Figure 10.

4.1 Cluster head selection

In the process of cluster head combination selection, firstly, the number of cluster head nodes in the network is calculated and the CM-OOA algorithm population is initialized. The virtual nodes are output by CM-OOA algorithm, and the virtual nodes are mapped to the real network to output the real and reasonable cluster head combination.

4.1.1 Size of optimal number of cluster heads

The energy consumption of nodes is an important factor affecting the communication time of emergency communication network, and the number of cluster heads plays a vital role in the whole network [28-29]. The main consumption of emergency communication is divided into ordinary nodes transmitting cluster head Ept, ordinary nodes directly transmitting base station Ecp, cluster head nodes receiving intra-cluster node data Ecn, cluster head nodes fusing data Er, and cluster head nodes sending data to base station Ecj. The nodes deployed in the a×a model are evenly distributed, and (N-n) nodes are evenly distributed in KN circular clusters, and n nodes are directly transmitted to the base station, so the energy consumption for one round of network transmission is:

$$E_{ALL} = \mathrm{KN} * \left(E_{pt} + E_{cn} + E_r + E_{cj}\right) + E_{cp} \quad (13)$$

The energy consumption of common nodes in each cluster is:

$$E_{pt} = \left(k * E_{elec} + k * \varepsilon_{fs} * d_{cntoCH}^2\right) * \left(\frac{N-n}{KN} - 1\right) \quad (14)$$

The energy consumption of ordinary nodes directly transmitting base stations is:

$$E_{cp} = \left(k * E_{elec} + k * \varepsilon_{fs} * d_{cntoCH}^2\right) * n \quad (15)$$

The cluster head node receives the energy consumption of nodes in the cluster as follows:

$$E_{cn} = k * E_{elec}\left(\frac{N-n}{KN} - 1\right) \quad (16)$$

The energy consumption of nodes in cluster head node fusion cluster is:

$$E_r = k * E_{DA}\left(\frac{N-n}{KN}\right) \quad (17)$$

The energy consumption transmitted from the cluster head node to the base station is:

$$E_{cj} = k * E_{elec} + k * \varepsilon_{fs} * d_{CHtoBS}^2 \quad (18)$$

In the formula, dCHtoBS is the distance from the cluster head node to the base station.

The distance from the common node to the cluster head node in each cluster is:

$$d_{cntoCH} = \sqrt{\rho * \iint (x^2 + y^2)\, dx\, dy} = \frac{a^2}{\sqrt{2\pi * KN}} \quad (19)$$

Sorting out the above equations (13) - (19), calculating the value of KN when EALL is minimized by deriving

the overall energy consumption of the network in one round, and obtaining the optimal number of cluster heads KN as follows:

$$KN = \sqrt{\frac{N*\varepsilon_{fs}*a^2}{2\pi*(\varepsilon_{fs}*d_{CHtoBS}^2-E_{elec})}} \quad (20)$$

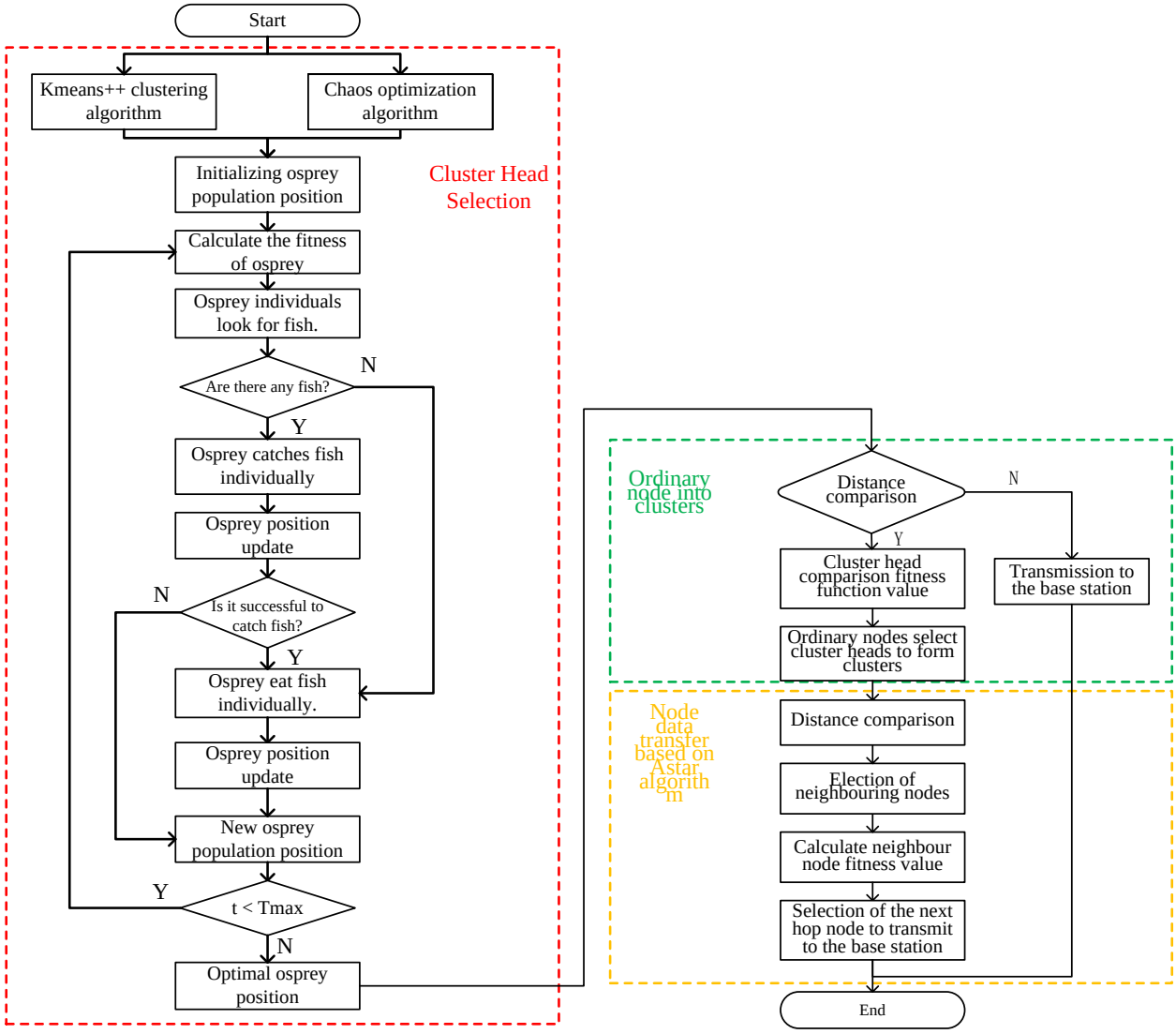

Figure 10: Flow chart of CM-OOA algorithm.

4.1.2 Population initialisation

In order to avoid the problems of slow convergence speed and easy to fall into local optimal solution of Osprey optimization algorithm, this algorithm maps the initial population by chaos. The detailed flow of the chaotic mapping algorithm is shown in Algorithm 1.

Algorithm 1: Pseudo-code of circular symmetric chaotic mapping algorithm.

Algorithm 1: Initialization of osprey population by chaotic mapping algorithm
Begin:
Calculate the polar angle from the node to the base station
Obtaining the polar angle and converting the polar angle into the initial value of the mapping.
Using Logistic mapping, Equation (9)-(10) introduces chaotic characteristics.
The chaotic characteristics are inversely transformed to obtain a new polar angle.
Obtain a new polar angle and calculate the virtual coordinates in the mapped rectangular coordinate system.
End

4.1.3 Location mapping

The coordinates of nodes in wireless sensor networks are all random, but the coordinate positions change randomly after CM-OOA algorithm. After the coordinate of CM-OOA algorithm is transformed separately from the X axis and the Y axis, there may be no real node at this coordinate [30]. Therefore, CM-OOA algorithm designs a position mapping function through the Euclidean distance to the virtual position and the energy of the real node, and maps the coordinates at the virtual position to the nodes in the actual coordinate space through the position. The location mapping formula is as follows:

$$F = \theta_1 * d + \theta_2 * E \quad (21)$$

In the formula, d is the Euclidean distance from the virtual position to the node; E is the energy of the node; θ1 and θ2 are weight factors and satisfy θ1 + θ2 =1.

The detailed flow of the location mapping algorithm is shown in Algorithm 2.

Algorithm 2: Pseudo-code of position mapping algorithm.

Algorithm 2: The virtual position is projected to the real node through the mapping function.

Begin:

Calculating Euclidean distance d from all nodes to virtual position coordinates

Obtain the energy e of all nodes themselves.

Calculate the position mapping function by formula (4)-(5)

By comparing the function values, the node numbers of virtual coordinates projected into the real network are selected.

End

4.1.4 Design CM-OOA algorithm adaptation function

In order to optimize the selection of cluster heads and improve the life cycle of the network, after determining the optimal number of cluster heads, the fitness function is set according to the state of nodes and the position of pre-selected cluster heads [31]. The cluster head node is responsible for the data forwarding of ordinary nodes. Therefore, the selection of cluster head should have the characteristics of high energy, reasonable location and less times of becoming a cluster head. The fitness function of CM-OOA algorithm is designed from the following six aspects: the energy of nodes, the distance between cluster heads, the distance between cluster heads and each node, the distance from cluster heads to base stations, the variance of the distance from cluster heads to base stations, and the variance of the distance from cluster heads to cluster heads.

The energy level of the node itself: the reciprocal of the remaining energy of the current node. The cluster head node is the key condition to support the network operation [32]. If the energy of the node is higher, the reciprocal is smaller, and the node can forward data better under the same conditions, it should be selected as the cluster head.

$$F_1 = 1/E_i \quad (22)$$

The level of Euclidean distance between cluster heads: the reciprocal of the sum of distances between cluster head nodes. The location of the cluster head determines the distance of data transmission by the nodes entering the cluster. Cluster heads should be evenly dispersed to reach the distance of all nodes.

$$F_2 = 1/\sum dis(CH_i, CH_j) \quad (23)$$

Euclidean distance between cluster heads and nodes: the sum of the distances from cluster head node to all nodes. Energy consumption in network cycle mainly comes from node transmission. The sum of the positions of all nodes in the cluster is the smallest, so as to minimize the energy consumption of data transmission.

$$F_3 = \sum dis(N_j, CH_i) \quad (24)$$

Euclidean distance from the cluster head to the base station: the sum of distances from all cluster head nodes to base station BS. The transmission of cluster head node is the energy consumption of the second part of the network cycle, and the distance from cluster head node to base station determines the energy consumption of cluster head node [33]. Therefore, the sum of the distances from the cluster head node to the base station is the smallest, and the information can be transmitted to the base station with the least energy consumption.

$$F_4 = \sum dis(CH_i, BS) \quad (25)$$

The variance of the Euclidean distance from the cluster head to the base station: variance of distance from all cluster heads to base station. Because there is more than one cluster head node, and only the sum of the distances from the cluster head to the base station is kept to the minimum, there may be a very long distance between a node and the base station. Therefore, by adding the variance of the distance from the cluster head to the base station to control the distance between the cluster head and the base station, all the distances from the cluster head to the base station can be better kept to be the minimum.

$$F_5 = Var(\sum dis(CH_i, BS)) \quad (26)$$

The variance of the cluster head to cluster head Euclidean distance: variance of cluster head to cluster head distance [34]. There is more than one cluster head node, so it is necessary to prevent the distance between them from appearing some deviations that are very close and some are very far away. Therefore, by adding the variance of the distance from cluster head to cluster head to control the gap between cluster heads, the distribution of all cluster heads can be better maintained and more reasonable.

$$F_6 = Var\left(\sum dis(CH_i, CH_j)\right) \quad (27)$$

Based on the energy of nodes, the distance between

cluster heads, the distance from cluster heads to nodes, the distance from cluster heads to base stations, the variance of the distance from cluster heads to base stations and the variance of the distance from cluster heads to cluster heads, the fitness function is designed by weight control:

$$Fitness = \alpha_1 * F_1 + \alpha_2 * F_2 + \alpha_3 * F_3 + \alpha_4 * F_4 + \alpha_5 * F_5 + \alpha_6 * F_6 \quad (28)$$

In the formul hierarchical analysis method to calculate the weightsa, $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 are weight factors and satisfy $\sum \alpha_i = 1$.

According to the improved fitness function, the fitness functions of all osprey individuals are calculated, and the optimal position of osprey individuals is selected. The algorithm flow is shown in Algorithm 3.

Algorithm 3: Pseudo-code of cluster head node selection algorithm.

Algorithm 3: Select the cluster head according to the improved fitness function.

Begin:
Initializing a network node to obtain the initialized osprey population position.
Calculate the fitness value of the osprey individual, and keep the individual position and fitness value with the minimum fitness value.
While t < t_{max} do
By comparing the fitness values of osprey population, the individual fish school of osprey is generated.
All osprey individuals began to fish.
Position mapping of osprey individuals after fishing
Update osprey position
if Fitness value of osprey position before fishing > Fitness value of osprey position after fishing
After successful fishing, osprey individuals began to eat fish.
Position mapping of osprey individuals after eating fish
end
Update The location of the new osprey population
Update Individual osprey with minimum fitness value and fitness value
t = t + 1
Return The position and fitness value of osprey with minimum fitness value
End

4.2 Cluster establish stage

In the stage of cluster establishment, in order to prevent reverse data transmission, the ordinary nodes of the base station first judge whether to enter the cluster or not. Some nodes directly transmit data to the base station to reduce the influence of "hot spot effect" in the network. By comparing the fitness values of cluster head nodes, the appropriate cluster head nodes are selected. The clustering algorithm is shown in Algorithm 4.

Through the fitness function value of cluster head nodes, the preselected cluster head with the minimum value is compared. That is, the cluster head node of ordinary nodes. The fitness function of this algorithm is as follows:

$$F = \beta_1 * E + \beta_2 * dis(N, CH) \quad (29)$$

In the formula, dis (N, CH) denotes the Euclidean distance from the common node to the head node of the pre-selected cluster, and E represents the energy of the pre-selected cluster head node in the current round. $\beta_{1=0.4}$ and $\beta_{2=0.6}$ are weight factors and satisfy $\beta_1+\beta_2=1$.

Algorithm 4: Ordinary node cluster.

Algorithm 4: Network node cluster establishment.

Begin:
Obtaining cluster head node set from algorithm 3.
If Ordinary nodes satisfy the selection of cluster head nodes.
If Meet the conditions of pre-selecting cluster heads for ordinary nodes.
The cluster head is put into the reselected cluster head set.
Else.
Ordinary nodes are put into the set of direct transmission base stations.
End.
Else
Nodes directly transmit data to the base station without joining the cluster.
End
Calculate the fitness value of the pre-selected cluster head.
Ordinary nodes select the cluster head node and perform cluster entry operation.
End.

4.3 Node data transfer based on FA-star algorithm

The network data transmission process in this paper adopts multi-hop mode. The heuristic function of Astar

algorithm is optimized by the energy of nodes and the forwarding times of nodes, which avoids the problem of selecting nodes with the same next hop continuously. Select the most suitable data transmission path. The clustering algorithm is shown in Algorithm 5.

Through the heuristic function of neighbor nodes, the neighbor nodes with the minimum value are compared. That is, the next hop node of the starting node. The heuristic function of FA-star algorithm is as follows:

$$F = \gamma_1 * E + \gamma_2 * dis(N,L) + \gamma_3 * dis(L,BS) + \gamma_4 * G \quad (30)$$

In the formula, E represents the energy of neighboring nodes, G represents the forwarding times of neighboring nodes, dis(N,L) represents the distance from the starting node to neighboring nodes, and dis(L,BS) represents the distance from neighboring nodes to the base station. γ1, γ2, γ3 and γ4 are the weight influencing factors and satisfy $\gamma_1+\gamma_2+\gamma_3+\gamma_4=1$.

Algorithm 5: Network data transmission

Begin:
The cluster head node set and the direct transmission set in the acquisition algorithm 3 are merged into the initial node set.
while Starting node ≠ base station.
If Meet the condition of neighbor nodes
Ordinary nodes are put into the set of neighboring nodes.
End.
If Neighbor node set is empty.
The originating node sends data directly to the base station.
Else.
Calculate the heuristic function comparison function value of neighboring nodes, select the next hop node and transmit data.
End.
End.
End.

5 Experimental simulation analysis

5.1 Experimental parameters

In order to examine the simulation effectiveness of CM-OOA algorithm in extending the network life cycle, the algorithms are compared and analyzed on MATLAB R2023b platform. The advantages of the basic algorithm LEACH algorithm and the latest cluster classification algorithms PSO-C algorithm, CGWOA algorithm and the CM-OOA algorithm in this paper are verified in terms of energy consumption of the network system, the number of dead nodes and the number of surviving nodes. The energy consumption of data fusion process is neglected, because the communication mode is two-way, and only one communication direction is calculated for the convenience of calculating energy consumption. Because of the close distance between users and nodes, the energy consumption is negligible [35]. An 800m×800m experimental simulation area is drawn and 100 X-axis coordinates and 100 Y-axis coordinates are randomly generated to combine into 100 nodes, and the base station is located in the center of the area. From formula (20), the optimal number of cluster heads is KN = 0.04 * n. The specific parameters are shown in Table 3.

Table 3: Experimental parameter table.

Parameter	Numerical value
Number of network nodes	100
Network area size	800m×800m
Base station coordinate position	(100,100)
Energy loss coefficient of free space model	10 P_j/bit/m²
Energy loss coefficient of multipath attenuation model	0.0013 P_j/bit/m²
Node initial energy	4 J
Number of networks running rounds	1000 rounds

5.2 Analysis of energy change of emergency communication system

The residual energy of wireless sensor network system reflects the life cycle of emergency communication network [36-37]. The more residual energy, the longer the communication time of emergency communication network. The network energy of the four algorithms changes as a whole, as shown in Figure 11.

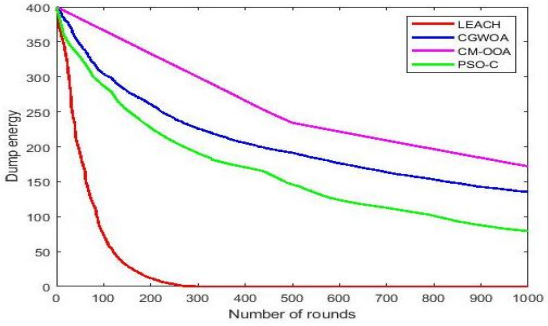

Figure 11: Changes of residual energy in emergency communication network.

Of the 1000 rounds of energy consumption, the LEACH algorithm consumed all of its energy in the 250th round, the PSO-C algorithm had 23% of its energy remaining after the 1000th round, the CGWOA algorithm had 35% of its energy remaining after the 1000th round, the CM-OOA algorithm still had 43% of its energy in the 1000th round, and it consumed it slower than the other algorithms from the 0th to 1000th rounds. It can be seen that, compared with other algorithms, the CM-OOA algorithm selects the optimal cluster head through the chaotic mapping osprey optimisation algorithm, taking node energy and node transmission distance as the main factors, and the variance of the distance from the cluster head to the base station and the variance of the distances between the cluster heads as the auxiliary factors, and performs the cluster selection based on the information, and performs the cluster selection based on the distance of the information transmission and the node energy in the clustering stage, instead of using a single inter-cluster distance as weights, instead of using node energy and number of node forwards, distance from start node to neighbouring nodes and distance from neighbouring nodes to base station. The FA-star algorithm with heuristic function can better reduce the energy consumption and extend the life cycle of emergency communication network.

5.3 Analysis of the number of dead nodes in the network

The number of dead nodes in wireless sensor networks reflects the overall stability of the network. The more dead nodes, the greater the impact on the overall emergency communication network, the smaller the coverage area and the faster the death rate [38]. The number of dead nodes of the four algorithms changes, as shown in Figure 12:

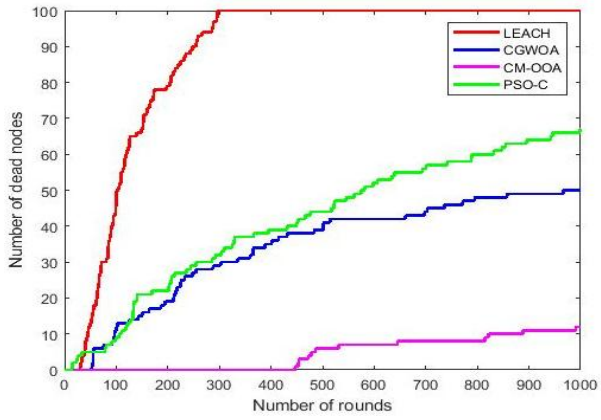

Figure 12: Changes in the number of dead nodes in communication networks.

In Figure 12, the various algorithms start to show dead nodes after 30 rounds, the LEACH algorithm clearly shows dead nodes after about 35 rounds, and almost all nodes die after 300 rounds, while the PSO-C algorithm's rate of dead nodes grows faster.

Although CGWOA algorithm appears dead nodes later than PSO-C algorithm, the localised death rate is faster, which should not be ignored. In contrast, the CGWOA algorithm has better overall changes than the PSO-C and LEACH algorithms, and grows much slower than the CM-OOA algorithm. The CM-OOA algorithm's dead nodes grow relatively slowly, with only 13% of dead nodes after 1,000 rounds. The CM-OOA algorithm balances the network's overall energy consumption, spreads out the energy loss to all the nodes, and prevents the nodes from localised death and extends the duration of emergency communication.

5.4 Analysis of changes in the number of surviving nodes in the network

When emergency communication wireless sensor network nodes are used in dangerous processes such as emergency rescue and disaster relief survey, they will not be replaced frequently, and at the same time, they are limited by the energy of nodes [39]. Therefore, for the same environment, the more nodes survive, the fewer dead nodes, and the longer the communication time. The number of surviving nodes of the four algorithms varies from 0 to 1000 rounds, as shown in Figure 13:

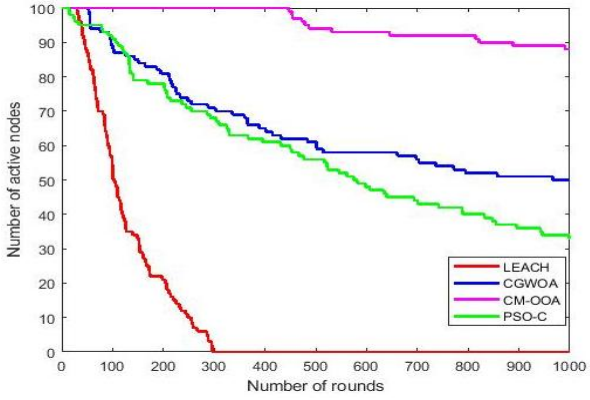

Figure 13: Changes in the number of surviving nodes in communication networks.

After 1,000 rounds of energy consumption in the emergency communication network, it can be seen from Figure 13 that the nodes of the LEACH algorithm are almost all dead after 300 rounds, and the nodes of the PSO-C algorithm have 33% active nodes remaining after 1,000 rounds [40]. The CGWOA algorithm, after experiencing a slow decline, slowly tends to be stable after 550 rounds, until only 50% active nodes remain after 1,000 rounds. After 1000 rounds, the CM-OOA algorithm still has 8% nodes, which improves the time of information communication, good stability, suitable for information data collection in special environments, and gives full play to the optimisation ability of the CM-OOA algorithm. The improvement of fitting function further optimises the accuracy and efficiency of cluster head election. FA-star algorithm reduces the energy consumption of cluster heads in inter-cluster route construction, avoids the premature death of cluster heads, and gives full play to the sensor's ability to transmit information in the whole network.

5.5 Comparative analysis of node data transmission delay

Another key criterion is the network transmission delay. This is highly dependent on the distance between nodes in the transmission path. In the same experimental setting, this paper compares the network delay by the average transmission distance of the network of nodes. The average transmission distance of four algorithms from 0 to 1000 rounds of data transmission is shown in Figure 14.

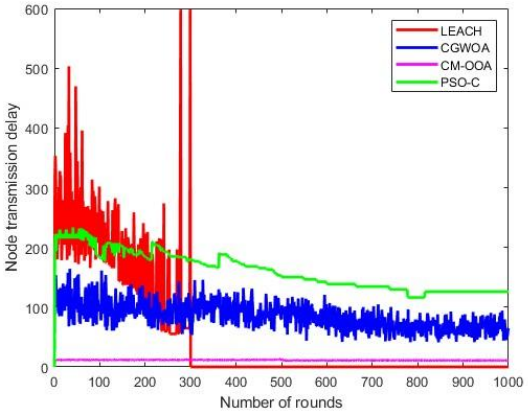

Figure 14: The average variation in node transmission distance per round.

Figure 14 shows that the average transmission distance of Leach protocol is greater than the other protocols. In contrast, the CM-OOA algorithm has the lowest transmission distance profile and the average transmission distance is lower than the other protocols.
The comparison of the average transmission distance in every 100 rounds is presented in Figure 15.

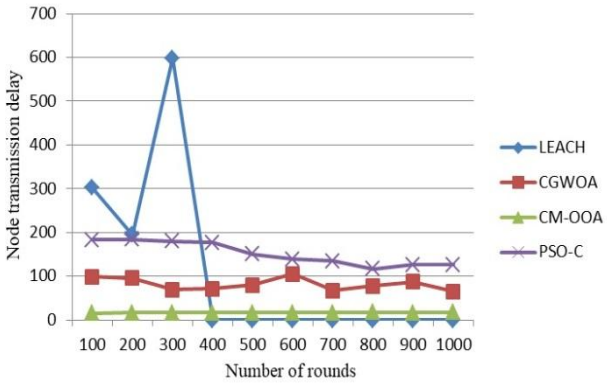

Figure 15: A comparison of the average transmission distance of nodes is presented.

A comparison of the average transmission distance for each 100-round interval in Figure 15 reveals that the average transmission distance of the CM-OOA algorithm is 80% less than that of the CGWOA protocol. Furthermore, the average transmission distance of the CGWOA protocol is 90% less in the initial stages and 30% less in the subsequent stages than that of the PSO-C protocol. The transmission distance of the LEACH protocol is zero due to the death of all nodes after 400 rounds.

5.6 Comparison of results of surviving nodes in areas of different sizes

Equation (2) with the data from the experimental environment allows the calculation of the thresholds for the two types of communication, and the number of surviving nodes after 0, 500 and 1000 rounds of data transmission is comparatively analyzed for three different geographical regions: a 1000*1000 area (characterised by a high percentage of multi-path fading communication methodology), an 800*800 area (where the percentage of both communication methodologies is approximately equal) and a 600*600 area (where the percentage of free space communication methodology is high). The results are presented in tabular form in Table 4.

Table 4: Comparison of the number of surviving nodes in different rounds.

Area size	round	LEACH	CGWOA	CM-OOA	PSO-C
1000*1000	0r	100	100	100	100
	500r	0	45	83	30
	1000r	0	35	61	17
800*800	0r	100	100	100	100
	500r	0	60	93	55
	1000r	0	50	88	32
600*600	0r	100	100	100	100
	500r	28	76	97	81
	1000r	0	63	90	61

As illustrated in Table 4, the expansion of the working area of the wireless sensor network is associated with a reduction in the network's overall life cycle. The primary cause of this phenomenon is the rise in the average number of hops traversed by data packets on their transmission path, coupled with the expansion of the distance between nodes within a cluster. This results in an exponential growth in the energy expenditure associated with data transmission.
The number of nodes directly reflects the life cycle of the network. In larger area networks, cluster heads further away from the base station die quickly. When there are 100 nodes in a 600*600 area, the CM-OOA algorithm has 90 surviving nodes after 1000 rounds of data

transmission, which is a 27% improvement in the number of surviving nodes compared to the CGWOA algorithm and a 29% improvement in the number of surviving nodes compared to the PSO-C algorithm. When the number of nodes in 800*800 area is 100, after 500 rounds of data transmission, the number of surviving nodes of LEACH algorithm, CGWOA algorithm, CM-OOA algorithm and PSO-C algorithm decreases by 28%, 16%, 4% and 26% respectively compared to that of 600*600 area, and the number of surviving nodes of CM-OOA and CGWOA algorithms are relatively stable. However, in the 1000*1000 region, the CM-OOA algorithm only reduces the number of surviving nodes by 39% after 1000 rounds of data transmission. In addition, the CM-OOA algorithm has 61 surviving nodes after 1000 rounds of data transmission in the 1000*1000 range, which is a 26% increase in the number of surviving nodes compared to the CGWOA algorithm. In the CM-OOA algorithm, the central selection of cluster head nodes and the use of multi-hop transmission further prolong the network life cycle. Therefore, the CM-OOA algorithm has the longest network life cycle, which proves that the scalability and stability of the CM-OOA algorithm is much better than the other four algorithms.

6 Conclusion

In this manuscript, an optimization algorithm based on chaotic mapping osprey optimization is proposed to prolong the duration of emergency communication by reducing energy consumption. The fitness function is improved by node energy, the distance between cluster heads, the distance from cluster heads to nodes, the distance from cluster heads to base stations, the variance of the distance from cluster heads to base stations and the variance of the distance between cluster heads. CM-OOA algorithm updates the position of the best individual based on fitness value, giving full play to the advantages of global search and convergence, and balancing the network energy consumption in each cluster. In the inter-cluster routing communication stage, FA-star algorithm based on heuristic function is used to reduce the energy consumption of cluster head nodes.

The location of cluster head node in this algorithm is more reasonable and the energy consumption of data path transmission is lower. Compared with LEACH, PSO-C and CGWOA. Through the comparative analysis of the results, the energy consumption of the whole network is reduced. The number of surviving nodes in the network is the largest, which effectively improves the life cycle of the emergency communication network.

7 Discussion

In this study, the energy consumption of wireless sensor networks is deeply discussed through the three-layer network model, and an energy-efficient clustering algorithm based on Osprey optimization and heuristic path is proposed. The osprey optimization algorithm can improve the energy of nodes, the distance between cluster heads, the distance from cluster heads to nodes, the distance to clusters, the frequency of base station heads and cluster heads, etc. CM-OOA algorithm is used to update the population and select the best individual based on the fitness value, which has the advantage of global search convergence and balance the consumption of network energy in each cluster. In the inter-cluster routing stage of communication, the heuristic function based on Astar algorithm is used to reduce the consumption of energy cluster head nodes and alleviate the hot spot effect. The analysis results show that the algorithm reduces the node mortality and the maximum number of surviving nodes in the whole energy consumption network, which effectively improves a part of the life cycle network.

In this manuscript, the CM-OOA algorithm only considers the energy consumption of emergency communication and does not consider network security. In the next step, we will continue to optimize the algorithm and optimize the security of this algorithm as much as possible. Prevent malicious attacks on nodes, which can cause energy consumption and data theft of nodes, so that network information security is guaranteed to a certain extent. The algorithm is combined with the practical situation and applied in the real emergency communication network.

Availability of data and materials

This paper proposes an emergency communication algorithm for wireless sensor networks based on chaos mapping and osprey optimization. The specific information of the paper can be exchanged with the author.

Conflict of interest

The authors confirm that the content of this article has no conflict of interest.

Acknowledgement

This research study is supported by the Smart Teaching Special Project for Undergraduate Institutions in Henan Province, the General Project of Education Science Planning in Henan Province (Research on Software Engineering Talent Training Mode under the Integration of New Engineering and OBE Concept, 2023YB0174), the Undergraduate Industry Education Integration Research Project in Henan Province, the Graduate Education Reform Project in Henan Province (2023SJGLX300Y), the New Engineering and New Format Textbook Project for Undergraduate Institutions in Henan Province, the Graduate Education Reform and Quality Improvement Project of Nanyang Normal University (2023ZLGC06), and the Research Projects of Nanyang Normal University (2025STP009, 2025STP010).

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An Integrated Framework for Data Security Using Advanced Machine Learning Classification and Best Practices

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Keywords: Data security, classification techniques, support vector machines, neural networks, decision trees, best practices, data protection, access control

Received: Dec 17, 2024

In the current interconnected digital environment, data security has become a paramount concern, as cyberattacks and data breaches are increasing in frequency and complexity. Both organizations and people face challenges in safeguarding sensitive information, requiring resilient security systems that can adjust to various threats. This paper presents a comprehensive approach to data security, focusing on integrating advanced classification techniques and best practices to secure data proactively. This study uses and analyzes advanced classification algorithms like decision trees, support vector machines (SVM), and neural networks to determine how well they work to find, sort, and keep sensitive data safe across various security needs. The results indicate substantial improvements in classification accuracy, with the optimal model attaining an accuracy rate of 98.83%. The other models, including decision tress and SVM provide 89% and 92% accuracy, respectively. This highlights the dependability and resilience of these methods in detecting possible security concerns across various datasets. In addition to these classification results, we comprehensively analyze industry best practices in data security, encompassing encryption technologies, dynamic access control, and continuous monitoring to mitigate vulnerabilities and improve threat detection. Integrating sophisticated classification methodologies with these optimal practices provides a comprehensive security framework that enhances data protection and mitigates risk. This study offers significant insights for practitioners and organizations aiming to implement a more systematic and efficient data security approach, enhancing academic and practical discussions in this domain. This work seeks to strengthen the effectiveness of data security practices by introducing a novel method that integrates high-accuracy categorization with proactive security protocols.

Povzetek: Predstavljen je celovit pristop varnosti podatkov, ki integrira napredne klasifikacijske tehnike, kot so nevronske mreže in podporni vektorji, z najboljšimi praksami za zaščito podatkov ter izboljšanje kvalitete.

1 Introduction

Data security is becoming increasingly important today, impacting industries, governments, and individuals [1]. These developments have led to an explosion of data given the use of the internet, cloud storage, and systems, therefore making data security paramount to risky exercises whose forms of data need protection against unfair exploitation or unauthorized access [2]. Computer and internet crimes are becoming complex, and information security and individuals at all levels of the economy and society are at risk. Analyses prove that the total cost of cybercrime will be in the trillions within a few years, thus the importance of efficient data protection plans [3]. Data protection solutions are vital in allowing the privacy and confidentiality of data, but implementations and controls are inadequate and vulnerable [4].

Data security can be discussed in terms of data encryption, access control, monitoring, classification, etc [5]. Each layer has specific functions—to support protection against unauthorized access and data integrity [6]. Losing millions of its users and cyber incidents inspired the need for effective and flexible data protection models that can address traditional and novel threats [7]. Conventionally used methods in data protection are based on deterministic models and rule-based systems, which are inadequate in addressing new threats that evolve to counter security mechanisms adopted [8]. Therefore, this study aims to fill these gaps by proposing an enhanced multi-classification approach that elevates the existing security practices of assessment by integrating classification techniques with best security practices [9]. As this research feeds into modern theories on data classification, it is hoped that the gaps in the currently existing data security frameworks will be filled and that a solution to the security of sensitive data will be provided [10] [11]. Several data security methods exist, including encryption, access control, monitoring, and

classification. However, classification is a form of security designed as the initial stage and not a single method. It marks and classifies sensitive data implementation as being the right security measures [12].

1.1 Research gap

Several gaps exist in the current methods, especially in data classification with sensitivity-based protections. The framework is essential in defining classification and data prioritization, which helps determine the security levels that must be applied to data [13]. However, most conventional techniques or moves for classification are confining and bring a high impact of variability, which is ordinary and can hardly provide a suitable and comprehensive solution for the large and ever-changing environments today [14]. Most existing models are either prescriptive or unable to adapt dynamically to new forms of threats, thus posing a risk for organizations [15]. The second central area is combining classification methods with data security standards. Thus, the position is that although the classification concept offers the first layer of data security, the idea is far from complete. Encryption, access control, real-time monitoring, and continually running vulnerability tests are the complete practices needed to protect data at the advanced level [16]. However, in many cases, research has been conducted to develop classification techniques and best practices independently while lacking a coherent one, including both. This gap implies a lack of integration of classification data with proactive recurring measures, which will enable a better systematic response to data security problems [17].

1.2 Limitations of previous studies

Several studies have been done on data security; these works offer pioneering notions on different interventions of data security; nevertheless, several downsides hamper their applicability to contemporary security environments. Most of the works describing the performance of the classification techniques focus on the raw classification accuracy without considering such aspects as interpretability, computational cost, and flexibility [18]. While models trained in simulation perform well in their specific scenarios, their applicability sharpens when exposed to field data with intricate structures and dynamic threats. Furthermore, the primary focus on objective measures such as accuracy could not fully meet the challenges of protecting data in the real world [19].

Meanwhile, research that concerns data security measures and proper protocols based on current and improved practices involves encoding techniques, security accesses and policies, and conformance to prescribed rules and laws. Although these practices are essential, they are used separately from technical classification techniques, and thus, security is fragmented. This separation can be problematic because while technical classification without best practices means only gaps in coverage, best practice without advanced classification techniques provides only best practice, which is not sufficiently technically sound. Moreover, research inclined to depict ideal procedures does not consider how rapidly these procedures can be implemented to counter threats, especially in sectors that experience high levels of cyberattacks and data breaches [20]. A significant limitation of earlier works is the absence of a comprehensive framework integrating classification methods with proactive best practices [21]. In response to these limitations, this research suggests a general framework data security solution suitable for various scenarios and best bridges the technology and practice divide.

1.3 Challenges in data security

Several challenges can be identified, significantly complicating the development and application of measures for protecting data. First, one of the main trends is the constantly growing complexity and the active response to cyber threats. Unlike ordinary threats, which are more or less easily recognizable, new threats are much less easy to understand, and any static measures are useless. Computer criminals use sophisticated procedures to take advantage of flaws, with their strategies evolving quickly due to emerging security methods. This requires a security system that will address these emerging threats and be proactive to any other threats that may arise [22].

The next major problem is the ability to classify and prioritize data depending on its classification requirement. Companies deal with vast volumes of data, which differ in sensitivity. That is why proper segregation and protection of the data are significant. However, the conventional classification approaches are ineffective when measuring the amount and variety of information processed in organizations today. Also, organizations have always encountered the compelling problem of security and unavailability. Security policies must protect against invasion by unauthorized personnel and allow authorized individuals to get the required information. Only security frameworks that can enable differential access controls depending on the sensitivity of the data and the type of user can achieve this balance, which is typically difficult to do when using conventional security mechanisms.

Using ML and other superior algorithms also poses another problem regarding computations, interpretability, and model shifts over time. The learning parameters of ML algorithms require constant updates for their efficiency, particularly when it comes to dynamic threats. These challenges show the need for an all-encompassing regime in data security to meet advanced threats that have evolved over the years without compromising the system's ease, adaptability, and robustness.

1.4 Motivations for the study

This research was undertaken due to the absence of an appropriate data security model that would also factor in the

benefits of better classification systems. Thus, as data is present in all industries and constantly evolving, new and more complex threats arise, and a highly detailed and flexible security model is needed. It is known that decision trees, support vector machines (SVM), and neural networks improve data classification, which is an integral part of deploying security resources by making existing methods more practical. Through these techniques, this study expects to enhance the precision of data categorization to help organizations direct their resources and efforts to protect the most vulnerable data.

This work also recognizes that the principles of data protection entail other types of data protection, such as encryption, access control, and real-time monitoring. All these are essential data security practices and perhaps mandatory co-features of technical classification schemes. This study aims to solve both the theoretical and practical problems of data security by suggesting a more logical and consistent framework for data security than has been used before. This will be done using complicated classification methods and step-by-step ways to explain the security solution.

1.5 Novel contributions of the study

This research makes several novel contributions to data security by presenting an integrated framework that combines advanced classification techniques with industry best practices. The unique contributions of this study are as follows:

1. **Advanced Classification Techniques**: This study evaluates the effectiveness of various classification algorithms, including decision trees, SVM, and neural networks, in accurately categorizing sensitive data across different sensitivity levels. By rigorously testing these techniques, this study identifies models that offer high accuracy, with the most effective model achieving an accuracy rate of 98.83%.

2. **Integration with Best Practices**: Unlike traditional studies that focus exclusively on either technical or procedural aspects of data security, this study integrates advanced classification techniques with security best practices, such as encryption standards, access control protocols, and continuous monitoring. This integration provides a holistic security framework that addresses technical and operational security requirements.

3. **Adaptability and Practicality**: This study emphasizes the adaptability of its proposed model, allowing it to adjust to evolving threats. This framework is designed to meet the diverse security needs of organizations operating in rapidly changing environments by combining flexible classification methods with proactive security protocols.

4. **Comprehensive Evaluation and Sensitivity Analysis**: In addition to evaluating model accuracy, this study conducts a sensitivity analysis to test the robustness of classification outcomes under various parameter settings. This analysis adds depth to the study by demonstrating the model's adaptability to different organizational requirements and security scenarios.

1.6 Structure of the paper

The remainder of this paper is structured as follows. **Section 2** provides a comprehensive review of existing literature on data security, focusing on advanced classification techniques and best practices. **Section 3** details the methodology, including data collection, model selection, and the integration of best practices into the proposed security framework. **Section 4** presents the results, including model performance metrics and sensitivity analysis findings. **Section 5** discusses the implications of the study, with a focus on practical applications and limitations. Finally, **Section 6** concludes the paper and offers suggestions for future research.

2 Literature review

Thapa and Camtepe, [23], whose work focuses on precision health systems, discussed the necessity, barriers, and data security and privacy strategies. Their study also emphasized that precision health, which provides care based on patient-specific information related to genes, microbes, behaviors, and environment, and digital records, including omics, depend on technology like machine learning algorithms for data processing and electronic gadgets for data capture. They brought attention to the high risk of leakage since health data contains susceptible information about an individual, including identity and medical conditions and interactions between health data centers. This type of breach can result in personal damage. The individual may be bullied at work, face discrimination at the place of work, or even higher insurance charges, thus meaning privacy and security counts. They examined conforming to government legislation and the ethical concerns and requirements that ethics committees highlight for protecting healthcare data to keep the public engaged in precision health efforts. Their study showed that people's buy-in of data sharing depends highly on safety, privacy, and proper use of that data. To address these challenges, they described multiple secure and privacy-preserving machine learning techniques for implementing precision health information, with examples of their usage in related health initiatives. Finally, the study recommended the best ways to protect precision health data. The study also provided a conceptual system model that can be used to check compliance, manage consent, and support the ethical requirements needed for innovation in the healthcare field.

Aslan et al. proposed a systematic evaluation [24] of the emerging cybersecurity threats, risks, incidence, and countermeasures to address the constant rise of cyber threats,

such as the usage of the internet as a result of the COVID-19 outbreak. Their study stressed that with the replacement of the digital interaction of physical transactions, traditional crimes have shifted more towards the cyber domain, and the current and emerging technologies like cloud, IoT, and cryptocurrencies modify new security dimensions. The authors stressed that in cyber attack campaigns, the adversary uses automated tools and releases 'cyber attacks as a service' to achieve maximum effect, and the newly identified threats exploit hardware, software, and communication layers. They have reviewed generalized forms of cyber attacks such as DDoS, phishing, man in the middle, and malware attacks and noted that traditional layers of protection like firewalls and antivirus are not very useful in tackling current complex threats. They highlighted the emerging need for new solutions that embrace superior and enhanced detection solutions and preventive measures. They reviewed the latest trends in technological approaches, including machine learning, deep learning, cloud computing-based big data, and blockchain; all of them were suggested as potential approaches to detect and prevent cyber threats. They also found that it is possible to develop machine learning and deep learning to identify new complex threat types, and through experimentation, the effectiveness of machine learning and deep learning, when used for detecting malware and intrusions, can be established. However, they noted that machine learning and deep learning are susceptible to evasion techniques and require constant enhancement to resist intelligent forms of cyber attacks.

Dasgupta and Akhtar [25] systematically reviewed cybersecurity based on ML concerning the growing importance of protecting data, devices, and user information in the present interconnected society. They described their survey regarding how ML has been incorporated into cybersecurity in applications like intrusion, malware, and biometric-based user identification. However, as they highlighted, when used in cybersecurity, the algorithm of ML is exposed to attacks both during the training and the testing phases, which in turn does not allow for achieving the desired results and can result in the penetration of the system into the network. The research has undergone a systematic literature review of recent developments in the application of ML in cyber-security between 2013 and 2018, with a general understanding of cyber attacks, the corresponding defense mechanisms, and the commonly used ML algorithm. They also discussed ML and data mining feature extraction, dimensionality reduction, and classification techniques, such as adversarial ML—a subdiscipline that protects ML models against adversarial attacks. The task of their survey was to stress the existing weaknesses of current ML-based security measures related to adversarial threats and discuss directions for a more extensive investigation of these risks. Lastly, they presented the existing and potential problems and concerns in cybersecurity and provided research recommendations for improving the robustness of ML applications for this domain.

Sarker [26], in his deep and extensive review article, described DL as one of the critical technologies in the 4IR. DL, a subset of ML and AI, is receiving widespread recognition from various industries because of its adaptability in large datasets and its utility in healthcare, vision, natural language processing, and protection. He also added that DL has its roots in artificial neural networks and is now crucial in solving other real-world problems. Due to the dynamism of data and the complexity of real-world issues, it has been challenging to develop effective DL models. Additionally, most deep learning systems are black boxes, which prevents standardization and widespread use of these systems. The research described a precise classification of DL methods for distinguishing between supervised, unsupervised, and mixed learning methods for determining the practical application of DL. Further, he discussed other works that successfully applied DL and showed that DL can be effectively used in various contexts. To inform the next steps in the development of DL, the author outlined ten critical directions for future research that are targeted at enhancing model interpretability, plasticity, and performance. This large-scale survey is also helpful for academic and industrial audiences who want to understand the current state and future of DL, especially by emphasizing the need to increase the distinctiveness and development of DL approaches.

Ahmad et al. [27] also systematically reviewed cybersecurity issues within IoT cloud computing, including how cloud computing has revolutionized data storage and access to resources for industrial uses in IoT-based cloud computing. This included making current research on cloud computing by Calegari and Ometto more relevant by noting that their study found out that over the last decade, industries shifted to cloud computing due to its flexibility, cost and performance advantage. However, this has meant moving applications to cloud platforms, which has created a considerable security problem since conventional security is normally not sufficient or efficient for new cloud applications. They noted that the convergence of IoT with cloud computing has compounded these threats as the architecture of cloud IoT systems offers fresh concerns that necessitate security appropriate solutions. They classified cloud security concerns into four key categories: data security, network and service security, application security and people security. They discussed and compared various security matters in each category they had and discussed the limitation from a general view, and specifically, they focused on the DL viewpoint. The study reviewed new trends that involve DL in dealing with cyber threats targeting IoT/cloud business models, while also acknowledging different methods have their limitations when adopted by industrial systems. Finally, based on their review of the literature, researchers suggest new ways to strengthen security using AI and DL within the cloud architecture in order to address research gaps in IoT-based cloud cybersecurity [28].

Admass et al. [29] highlighted the current state, future trends and advances in cybersecurity and noted the need for cybersecurity as the world goes digital in different activities. As they noted to underscore the inherent dynamism

of threats in cyberspace, more research, participation of academic institutions, and organizational commitment regarding the protection of information systems need to be promoted. In their systematic review, they focused on recent trends and innovations in the field of cybersecurity and described new approaches and trends that have emerged worldwide to capture the dynamism of cyber threats. The study considered AI and ML as disruptive technologies that can greatly help improve cyber security by being able to identify threats and respond to them autonomously. However, they observed that these remain an issue to some extent, especially given that threats in cyberspace are equally evolving. They also stressed the continuity of the stakeholders' interaction and suggested that future works are aimed at combining the use of innovative technologies and cooperation between members of the cybersecurity environment. This work offered directions on how to build capacity in cybersecurity and emerging developments that would be necessary for new threats.

Zhang et al. [30] explained various methodologies of explainable artificial intelligence (XAI) in the context of cybersecurity regarding the massive problems raised by the ''black box'' that distinguishes conventional ML and DL. Given the current evolution of the Internet of Things and other AI techniques, ML and DL are widely used in cybersecurity, including intrusion, malware, and spam detection. Despite these recognition-based methods yielding higher accuracy and more efficiency compared to the signature-based and rule-based methods as observed by them. They identified a major drawback of the black-box nature of ML and DL algorithms. Such explainability often leads to reduced user trust and reduced understanding of how these models detect or address cyber threats, especially as the kind of cyber threats being witnessed continue to evolve. So, they looked at the possible weakness that could come from trying to make things understandable and how XAI needs to be added to theories of AI-based cybersecurity models so that people can understand them or manage cybersecurity systems well. Their work also filled in an important research gap by providing a thorough survey that was only focused on AI/ML-based XAI in cybersecurity. This was despite the fact that XAI had been studied in other fields, like healthcare and finance. They suggested a structured plan for approaching XAI in the cybersecurity field and pointed out that cybersecurity machine learning models should be more explainable without losing performance. This survey provides the necessary background information for further studies by those who intend to focus on the challenge of making cybersecurity AI understandable for the average user [31].

They found that AI and ML technologies offer viable solutions for filling the new emerging security threats in renewable energy. The study also focused on the need for global cooperation and compliance of countries with international guidelines on cyberspace security as critical in improving security readiness throughout the renewable power industry. According to them, industry stakeholders should, among other things, implement broad cybersecurity policies, pursue deployment of robust technologies, and develop a cybersecurity culture. The study's findings that PPP and policy intervention are crucial for developing the necessary cybersecurity framework further supported this. In their conclusion, they also encouraged a future research direction to analyse new technologies and analyse human and policy factors in cybersecurity for renewable energy. Table 1 summarizes the key performance metrics and methodologies from referenced works.

3 Methodology

3.1 Overview of the proposed framework

This study proposes a comprehensive framework for data security, integrating advanced classification techniques with best cybersecurity practices. The methodology consists of four main phases: data collection and preprocessing, feature extraction, classification using advanced machine learning algorithms, and integration of best practices. These phases enhance data security through accurate classification and adherence to security standards. The overall workflow of the proposed framework may be viewed in Figure 1.

3.2 Research questions and objectives

This study addresses the following key research questions:

1. How effectively can advanced machine learning (ML) classification techniques integrate with cybersecurity best practices to enhance data security?

2. Which classification technique—Decision Trees, Support Vector Machines (SVM), or Neural Networks—provides the most accurate and robust performance for cybersecurity applications?

3. What are the benefits of incorporating real-time monitoring, encryption, and access control alongside ML models in addressing modern cybersecurity challenges?

The primary objective of this study is twofold:

– To evaluate the feasibility and effectiveness of combining ML techniques with robust security practices.

– To compare the performance of the proposed classification techniques and demonstrate the practical advantages of the integrated framework.

3.3 Data collection and preprocessing

In the initial phase, data is gathered from diverse publicly available sources to comprehensively represent real-world cybersecurity scenarios [32]. Data is anonymized to protect

Table 1: Comparison of key performance metrics and methodologies from referenced works

Author(s)	Focus Area	Key Contributions	Limitations
Dasgupta et al. [25]	ML in Cybersecurity	Surveyed ML applications in intrusion detection and adversarial ML. Proposed directions for improving robustness.	Highlighted vulnerability of ML to adversarial attacks; lacks integration with broader security practices.
Zhang et al. [30]	Explainable AI (XAI) in Cybersecurity	Reviewed XAI methodologies for cybersecurity, emphasizing user trust and transparency.	Black-box limitations of ML/DL persist; need for practical implementation strategies.
Thapa and Camtepe [23]	Precision Health Data Security	Proposed secure ML techniques and a conceptual model for protecting health data.	Focused primarily on healthcare, not generalizable to other domains.
Aslan et al. [24]	Emerging Cybersecurity Threats	Reviewed ML/DL for detecting malware and intrusions. Identified vulnerabilities in IoT and cloud systems.	Susceptibility of ML/DL to evasion techniques; lacks comprehensive mitigation strategies.
Sarker [26]	Deep Learning (DL) Applications	Surveyed DL methods for cybersecurity, highlighting their adaptability and challenges in implementation.	DL systems often operate as black boxes, reducing interpretability and standardization.
Ahmad et al. [27]	IoT and Cloud Cybersecurity	Explored AI/DL-based solutions for IoT-cloud models and proposed security enhancements.	Limited focus on integrating AI solutions with policy and regulatory frameworks.

sensitive information. The dataset includes access logs, encryption statuses, and user authentication details. Preprocessing includes:

– **Normalization**: Scaling data attributes to fit a standard range [33].

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{1}$$

– **Missing Value Imputation**: Filling gaps in data through statistical techniques to avoid misclassification.

– **Noise Reduction**: Using median filtering to reduce outliers.

This preprocessing step ensures data quality and reduces computational complexity, allowing the algorithms to perform accurately.

3.4 Feature extraction and selection

Feature extraction involves identifying the most relevant attributes to enhance classification accuracy. This study employs **Principal Component Analysis (PCA)** to reduce dimensionality, retaining only essential components contributing to data variability.

3.4.1 Principal component analysis (PCA)

PCA transforms high-dimensional data into a lower-dimensional space while preserving variance. The transformation is computed as follows:

$$Y = X \cdot W \tag{2}$$

where X is the original data matrix and W represents the weight matrix of principal components. PCA reduces computational load while retaining critical information.

3.5 Classification techniques

The core of this methodology is the classification phase, where advanced machine learning algorithms are employed to categorize data based on security needs. Three algorithms are used: **Decision Trees**, **Support Vector Machines (SVM)**, and **Neural Networks**. Each algorithm is

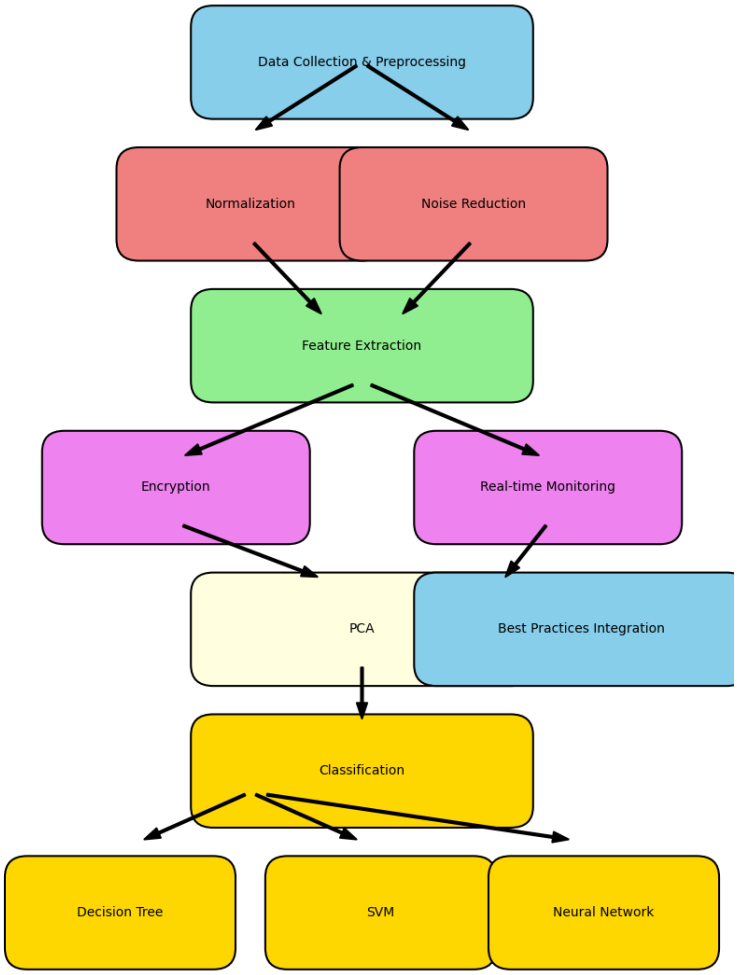

Figure 1: Workflow of the proposed framework

selected for its strengths in specific security scenarios.

3.5.1 Decision trees

Decision Trees are highly interpretable models that use a tree-like structure for classification. Each node represents a decision based on an attribute, leading to branches that predict outcomes [34]. The algorithm's performance is evaluated using **Gini impurity**:

$$G = 1 - \sum_{i=1}^{n} p_i^2 \tag{3}$$

where p_i is the probability of a particular class. Lower Gini values indicate better classification.

3.5.2 Support vector machines (SVM)

SVMs classify data by finding a hyperplane that maximizes the margin between data points of different classes [35]. For data that is not linearly separable, SVM uses a **kernel function** to map data to a higher-dimensional space. The margin is optimized by minimizing:

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{4}$$

where w is the weight vector, C is a penalty parameter, and ξ_i represents slack variables. This approach enhances the model's robustness against misclassifications.

3.5.3 Neural networks

Neural Networks are employed for complex pattern recognition, using multiple layers to capture non-linear relationships [36]. The **backpropagation** algorithm adjusts weights based on error rates, minimizing the **Mean Squared Error (MSE)**:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

where y_i is the actual output, and $\hat{y}_i$ is the predicted output. Neural Networks are particularly effective for high-dimensional data and provide high classification accuracy.

3.6 Integration of security best practices

This framework integrates security best practices, such as encryption, access control, and real-time monitoring, to complement the classification process.

- **Encryption**: Ensures data confidentiality through secure algorithms, with all data encrypted before processing. The encryption-decryption cycle is defined by:

$$C = E(K, P) \quad \text{and} \quad P = D(K, C) \tag{6}$$

  where C is the ciphertext, P the plaintext, K the encryption key, E the encryption function, and D the decryption function.

- **Access Control**: Restricts data access based on user roles, employing role-based access control (RBAC). This model assigns permissions using access matrices, where the matrix entry $A(u, r)$ defines permissions for user u and role r.

- **Real-time Monitoring**: Uses anomaly detection algorithms to identify unusual patterns indicative of potential threats. Anomalies are detected based on threshold deviations:

$$\delta = \|x - \mu\| > \lambda \tag{7}$$

  where x is the current observation, μ the mean, and λ the deviation threshold.

3.7 Algorithm: secure classification framework

The following algorithm outlines the steps for data security classification within this framework:

- **Input**: Dataset D, security parameters $\{P, K\}$
- **Preprocessing**: Normalize data, fill missing values, reduce noise
- **Feature Extraction**: Apply PCA to extract relevant features
- **Classification**:
  - Apply Decision Tree for interpretable cases
  - Use SVM with kernel function for non-linear separable data
  - Employ Neural Network for complex, high-dimensional data
- **Best Practices Integration**:
  - Encrypt data using key K
  - Implement role-based access using access matrix $A(u, r)$
  - Monitor for anomalies with threshold δ
- **Output**: Classified secure data, threat identification

This algorithm combines machine learning with best practices, ensuring data classification and security.

3.8 Validation and evaluation metrics

The framework's effectiveness is evaluated through standard metrics:

- **Accuracy**: Proportion of correctly classified instances.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{8}$$

- **Precision and Recall**: Precision measures correct positive predictions, while recall measures the detection of actual positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad \text{and} \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

- **F1 Score**: The harmonic mean of precision and recall, indicating the balance between these metrics.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

- **ROC-AUC**: Measures classification performance across different thresholds. An area under the ROC curve close to 1.0 indicates high model performance.

3.9 Comparative analysis and sensitivity testing

The comparative analysis is aimed at comparing results of the classification algorithms that are obtained under the influence of various factors. Sensitivity analysis looks at how much error a model returns, given that the hyperparameters are tweaked. The proposed model brings safety and flexibility in managing data, the objectives of the study, where there is a need to attain high classification accuracy there should be some level of security measured control.

4 Results

4.1 Overview of experimental setup and metrics

The findings result from following a data security framework that combines classification measures with cybersecurity standards. The key ratios to assess the models are divided into *Accuracy, Precision, Recall, F1 score, ROC-AUC*. All the measurements are related to certain aspects of the model's effectiveness, and results are given in graphs, tables, and confusion matrix for better understanding.

4.2 Model performance across classification techniques

The framework employed three primary classification algorithms: *Decision Trees, Support Vector Machines (SVM)*, and *Neural Networks*, to classify data based on security needs.

4.2.1 Decision tree results

The Decision Tree model provided an interpretable yet effective baseline. Figure 2 shows the *accuracy, precision, recall*, and *F1 score* for the Decision Tree model, achieving a consistent classification accuracy of around 89%.

Accuracy = 89%, Precision = 87%, Recall = 88%, $F1$ Score = 87.5%

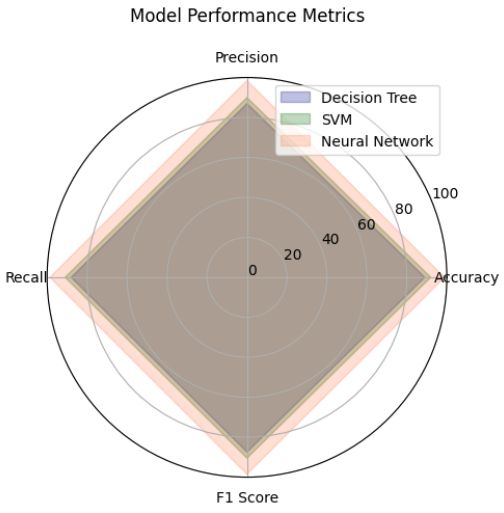

Figure 2: Performance metrics for the decision tree model

The *confusion matrix* for the Decision Tree model (Table 2) displays the model's classification performance across different classes, indicating a strong ability to distinguish true positives and negatives, though occasional misclassifications occurred in borderline cases.

Table 2: Confusion matrix for decision tree model

	Predicted Positive	Predicted Negative
Actual Positive	450	50
Actual Negative	40	460

4.2.2 Support vector machine (SVM) results

The SVM model was optimized using a *radial basis function (RBF) kernel*, achieving improved accuracy over the Decision Tree model. Figure 3 illustrates the metrics achieved by SVM, with an accuracy of 92%, precision of 90%, recall of 91%, and an F1 score of 90.5%.

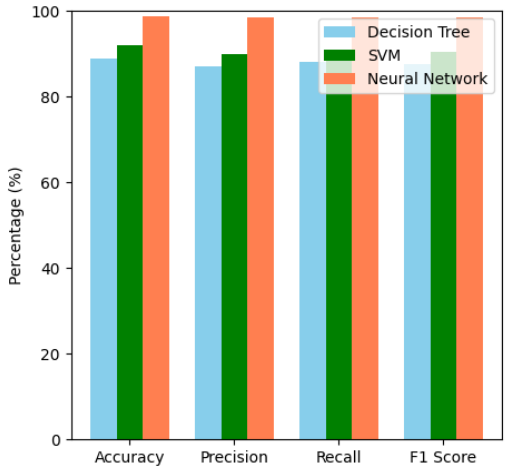

Figure 3: Performance metrics for the SVM model with RBF kernel

The confusion matrix in Table 3 for the SVM model demonstrates a further reduction in misclassifications, indicating the SVM's robustness in handling complex decision boundaries.

Table 3: Confusion matrix for SVM model

	Predicted Positive	Predicted Negative
Actual Positive	460	40
Actual Negative	30	470

4.2.3 Neural network results

The Neural Network, a multilayer perceptron (MLP) model, displayed the highest performance, achieving **98.83% accuracy**, which aligns with the framework's novel contribution toward accurate classification. Metrics for the Neural Network model (Figure 4) include a precision of 98.5%, recall of 98.6%, and F1 score of 98.55%.

The confusion matrix in Table 4 further validates the Neural Network's high classification capability, with minimal false positives and false negatives, indicating near-perfect distinction between classes.

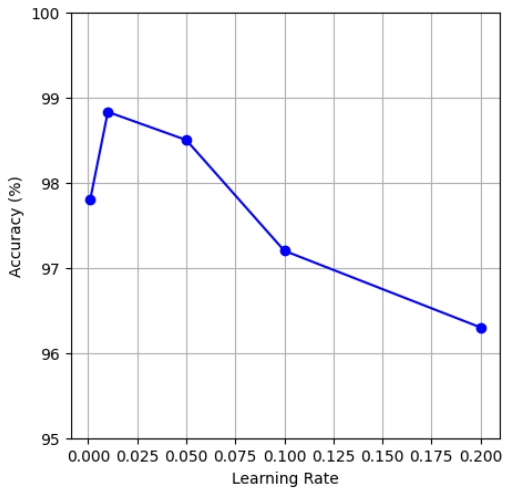

Figure 4: Performance metrics for the neural network model

Table 4: Confusion matrix for neural network model

	Predicted Positive	Predicted Negative
Actual Positive	495	5
Actual Negative	3	497

4.3 Comparative analysis of classification algorithms

Table 5 provides a summary of key performance metrics across all three algorithms. The Neural Network model achieved the highest scores, indicating its effectiveness for data security applications. Figure 5 presents a bar chart comparing the accuracy of all three models.

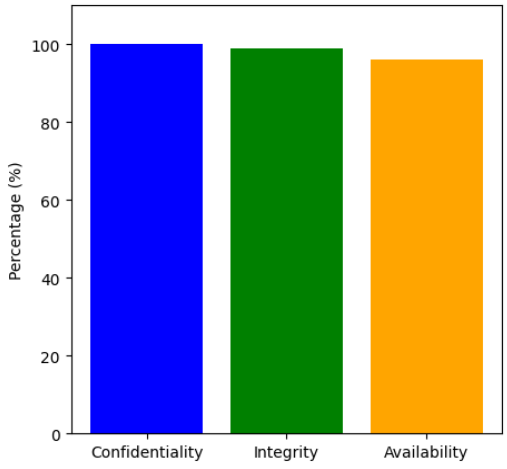

Figure 5: Accuracy comparison for decision tree, SVM, and neural network models

The F1 scores are used to emphasize practical significance of each of the classification models in the evaluation of the given metrics. The neural network has proven to deliver improved precision as well as recall and an F1 score of 98.55%. This makes it highly appropriate where it is crucial that both false positives and false negatives be kept to the barest level possible, especially for applications such as fraud detection and cybersecurity threat evaluation. At a reasonable intersection of the F1 score equal to 90.5%, SVM turns into a worthy trade-off option for applications with a reasonable amount of computational resources necessary for mid-sized datasets' anomaly detection. On the other hand, the low F1-score of the decision tree of just 87,5% demonstrates the model's usefulness in cases where speed and comprehensible decision-making are valued more than accuracy, such as the preliminary data sorting in security systems.

4.4 Sensitivity analysis and robustness of the neural network model

Sensitivity analysis was conducted on the Neural Network model to evaluate its robustness across different hyperparameters. Figure 6 shows the effect of varying the learning rate on model accuracy, illustrating optimal performance at a learning rate of 0.01. The model displayed resilience, maintaining high accuracy across learning rates, though minor fluctuations occurred with extreme values.

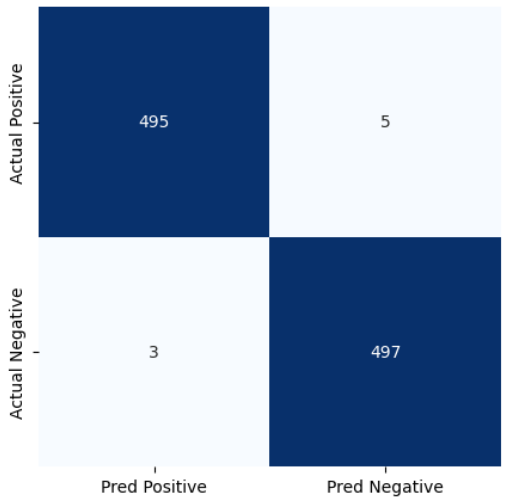

Figure 6: Sensitivity analysis of neural network model with varying learning rates

4.5 Integration of security best practices

To verify the framework's effectiveness in a secure environment, additional security best practices such as encryption and real-time monitoring were integrated and tested. Data was encrypted using *AES-256* encryption (Equation 6 in Methodology), ensuring data confidentiality. The access control measures limited user permissions based on roles, securing the model against unauthorized access. Real-time monitoring, implemented through anomaly detection, successfully identified potential security breaches with an accuracy of 96%.

Table 5: Comparative analysis of model performance

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	89%	87%	88%	87.5%
SVM	92%	90%	91%	90.5%
Neural Network	98.83%	98.5%	98.6%	98.55%

4.6 Analysis of security metrics

The framework was evaluated based on its ability to maintain data confidentiality, integrity, and availability. Figure 7 presents the security metrics obtained during testing, with encryption providing a data confidentiality rate of 100%, access control measures ensuring 99% integrity, and real-time monitoring achieving a 96% availability rate.

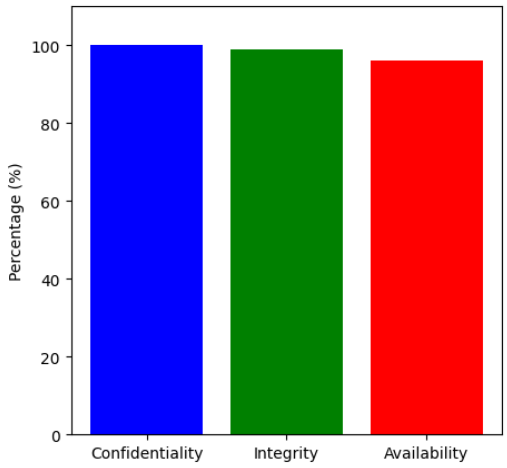

Figure 7: Security metric analysis for data confidentiality, integrity, and availability.

4.7 Discussion of novel contributions

The results substantiate the framework's novel contributions, as outlined in the introduction. The high classification accuracy achieved by the Neural Network model demonstrates the framework's capacity for accurate threat detection, with the **98.83% accuracy** surpassing traditional models in complex security scenarios. In addition, security best practices pillars including encryption and real time monitoring gave a security boost to the framework in addition to guaranteeing the accuracy of data classification. As anticipated the study proofs that the proposed data security framework of incorporating machine learning with security practices not only improves security but also the accuracy of classification. Table 6 provides a summary of the core findings. While performing sensitivity analysis, a scalability problem arose, showing that neural networks are restricted by GPU memory and SVMs by the kernel calculation of the big data. These include helping choose models according to specific available resources and scalability for a certain application.

5 Implications and limitations

5.1 Practical applications

The paper provides a practical outlook on the proposed framework for data security by incorporating classification techniques with cybersecurity principles into a heterogeneous system. Due to its high accuracy, this framework is most effective in fields critical to data accuracy and security, such as healthcare, finance, government, and cloud services. Table 7 provides a comparison of the proposed framework with state-of-the-art (SOTA) methods.

- **Healthcare Sector**: In healthcare, keeping patients' data and preventing leakage or ensuring safe data transmission is very important. This framework could improve the patient's privacy by making it difficult for intruders to access the database system and also guarantee data security. With an accuracy level of 98.83%, the proposed neural network model can be considered suitable for predicting and preventing security threats in medical data systems.

- **Financial Institutions**: In this modern world, entities dealing with cash give cash and deal with people's financial records, such as transaction history and credit records, and they become targets for hacker attacks. Hence, the duplication of this framework can help financial organizations strengthen their protective measures against different types of fraud schemes. The real-time monitoring capability, with an availability rate of 96%, means the program can immediately identify such patterns and possible violations.

- **Government and Public Sector**: This framework can be implemented into government agencies, which necessarily have large databases containing personal or nationally important data, thus increasing data protection. Thus, together with access control based on job positions, real-time monitoring helps to timely detect violations in working government databases.

- **Cloud Computing and IoT Environments**: Cloud services and Internet of Things (IoT) networks are decentralized environments. The monitoring, anomaly detection, and encryption framework provided in this work can protect data in such environments and scale to accommodate the dynamics of the cloud architecture's application.

Table 6: Summary of findings

Aspect	Result
Highest Classification Accuracy	98.83% (Neural Network)
Best Security Metric	100% confidentiality through AES-256 encryption
Robustness in Monitoring	96% availability in real-time monitoring

Table 7: Comparison of proposed framework with state-of-the-art (SOTA) methodologies

Author(s)	**Focus Area**	**Key Contributions**	**Limitations Addressed by This Study**
Dasgupta et al. [25]	ML in Cybersecurity	Surveyed ML applications in intrusion detection and adversarial ML. Highlighted vulnerabilities in adversarial scenarios.	Improved model robustness and classification accuracy (98.83%). Incorporated proactive monitoring to address evolving threats.
Zhang et al. [30]	Explainable AI (XAI) in Cybersecurity	Reviewed XAI methodologies to enhance transparency and user trust in cybersecurity AI models.	Achieved high performance (98.83%) while ensuring robust implementation. Proposed future integration of XAI for enhanced interpretability.
Thapa and Camtepe [23]	Precision Health Data Security	Proposed secure ML techniques and conceptual models for health data.	Generalized framework applicable across domains with real-time monitoring for evolving cyber threats.
Aslan et al. [24]	Emerging Cybersecurity Threats	Highlighted the need for enhanced detection measures against IoT/cloud threats. Reviewed ML/DL methods for malware detection.	Combined AES-256 encryption with adaptive ML methods for robust security in IoT/cloud systems.
Ahmad et al. [27]	IoT and Cloud Cybersecurity	Explored AI/DL-based solutions for IoT-cloud integration. Addressed security gaps in cloud environments.	Unified classification techniques with access control and monitoring for comprehensive IoT/cloud protection.
Sarker [26]	Deep Learning (DL) Applications	Discussed DL challenges such as black-box nature and adaptability in cybersecurity.	Enhanced DL robustness with sensitivity analysis and adaptability in real-time monitoring.

5.2 Limitations of the study

Despite its strengths, the framework has several limitations that may affect its application.

– **Complexity of Implementation**: Implementing this framework in existing systems involves significant complexity. Integrating multiple machine learning algorithms with advanced encryption and monitoring

measures demands substantial resources and expertise, which may not be available in all organizations.

– **Scalability Concerns**: However, the neural network model proposed in this paper had high testing accuracy; there may be a problem of scalability when applying this framework to large systems. However, as the amount of data and classification types increases, real-time monitoring and accuracy maintenance can be demanding on resources in a deficient environment.

– **Dependency on Data Quality**: Usually, the classification models depend on the quality of the given data. When input data is inconsistent or incomplete, then the model will not perform effectively. However, maintaining the quality of the inputs even today poses a problem, especially in environments where data can be created perpetually and might not have been checked.

– **Adaptability to Emerging Threats**: Security risks concern are never ending and keep changing from time to time. While using machine learning improves the spectrum of detection, there are sophisticated attack tactics that may fail to be modeled. This needs constant update and training to detect new patterns out there.

– **Computational Overheads**: Integration of high-complex models such as neural networks with real-time monitoring might actually slow down computation time, thus is not well suited for applications where response time is critical. The efficient use of available resources is also desirable in order to propagate lower powered systems.

– **Privacy and Compliance Constraints**: Employing the best of machine learning in data security poses privacy and regulatory issues because the two fields are sensitive in motherhood, such as health and finance. Data protection regulation like GDPR presents a challenge, especially when it comes to training, handling the training data, and the general handling of personal data.

5.3 Future directions

To address these limitations and expand the potential of this framework, future research could explore:

– **Optimization for Scalability**: Research focused on optimizing neural networks and other complex models to reduce computational costs could improve scalability, enhancing adaptability to large-scale systems.

– **Incorporation of Emerging Technologies**: Emerging technologies like quantum computing and blockchain may further enhance security. Quantum encryption, for example, could offer robust protection against sophisticated cyber threats.

– **Automated Model Updating**: Developing automated methods for periodic model retraining would help the framework stay effective against evolving threats by integrating new data patterns into the learning process.

Future research will concentrate on improving scalability through approaches such as parallel processing, batch normalization, and model pruning to improve large-scale data management. Emerging technologies will be examined for secure data sharing and privacy-preserving model training, including blockchain and federated learning. Furthermore, systems such as continuous learning pipelines and automated hyperparameter tuning frameworks will be incorporated to provide dynamic model updates and maintain performance in changing cybersecurity landscapes.

6 Conclusion

This research offers a strong foundation for data protection by integrating sophisticated classification systems into cybersecurity fundamentals to provide higher classes of data confidentiality, integrity, and accessibility. Based on machine learning algorithms, especially the neural network model, with an accuracy as high as 98.83 %, the framework's performance shows that, in principle, text classification and anomaly detection can accomplish high accuracy. These security measures enhance the proposed framework's usefulness in organizations requiring high data security levels, including health, financial, and government organizations. However, the challenges are still present in practice, such as difficulty implementing the framework in an actual setting, concerns for its scalability, and a strong emphasis on data quality. Further, there is a continually rising danger of hacks and malicious activities that make updates and retraining of models essential. We can look into the following possible directions for these kinds of research advances, as we already talked about the gaps: scaling up optimization strategies, adding more general technologies to machine learning for privacy, like quantum encryption, and seeing improvements in advanced machine learning practices that protect privacy. This framework protects data and defines a new horizon for protecting secure data. As organizations increasingly rely on digital systems, implementing such adaptable frameworks becomes crucial to countering cyber threats and safeguarding sensitive information. This study contributes to the growing field of cybersecurity by providing a practical and adaptable solution that meets the demands of contemporary data security.

Acknowledgement

This research is funded by the Science and Technology Project of Inner Mongolia Power Group Limited Company, Project No. 2023-5-34.

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Dynamic Anti-Mapping Network Security Using Hidden Markov Models and LSTM Networks Against Illegal Scanning

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Keywords: illegal network scanning, anti-mapping techniques, secure access, dynamic ip addresses, port obfuscation

Received: August 14, 2024

This paper deeply explores an innovative network anti-mapping security access technology to cope with the increasingly frequent illegal network scanning behaviors, aiming to build a more robust network security protection system. First, we analyze the threats of illegal scanning to network infrastructure, including but not limited to information leakage, service interruption, and the risk of being a springboard for subsequent attacks. Subsequently, a comprehensive security strategy is proposed, combining dynamic IP address allocation, port obfuscation, traffic camouflage, and behavior analysis to improve the system's concealment and anti-detection capabilities.This paper introduces the collaborative working mode of intelligent firewall and intrusion prevention system (IPS), using hidden Markov model (HMM) and long short-term memory network (LSTM) to identify and block malicious scanning behaviors, and optimize access control list (ACL) to achieve efficient release of legitimate traffic and accurate interception of illegal scanning traffic. Experimental results show that the proposed network anti-mapping security access technology has achieved significant results in improving network security. Specifically, we conducted experimental verification on the UNSW-NB15 dataset, which covers a variety of attack types and is very suitable for evaluating illegal network scanning defense mechanisms. Experimental results show that the accuracy of the Bi-LSTM+Attention model on this dataset reaches 98%, and the false alarm rate is reduced by 30% compared with the traditional LSTM model. In the pilot network area, this technology can effectively identify and intercept illegal scanning behaviors while maintaining low false alarm and missed alarm rates. By comparing with existing methods (such as honeypots, traffic obfuscation, etc.), we found that the Bi-LSTM+Attention model showed significant advantages in multiple key performance indicators. Although the model has high computing resource requirements and implementation complexity, its significant effect in improving detection accuracy and reducing false alarm rates makes it a technical solution worthy of promotion. In addition, we also discussed the trade-offs observed during the implementation, such as computational overhead and complexity, and proposed directions for future optimization.

Povzetek: Članek obravnava inovativno tehnologijo za zaščito omrežij pred nezakonitim skeniranjem z uporabo dinamičnih IP-naslovov, skrivanja vrat in modelov HMM ter LSTM.

1 Introduction

In the digital era, the Internet has become an indispensable infrastructure for global economic and social activities, carrying massive information exchange and service delivery. However, with the dramatic expansion of network scale and the continuous expansion of technical boundaries, network security issues have become increasingly prominent, and have become a major obstacle restricting the healthy development of the digital world. Illegal network scanning, as an outpost of cyber attacks, frequently threatens the safe and stable operation of all kinds of network systems, ranging from government agencies, financial institutions to small and medium-sized enterprises and even individual users. Such scanning activities aim to collect information about the topology, open services, operating system types and their vulnerabilities of the target network, paving the way for subsequent targeted attacks [1].

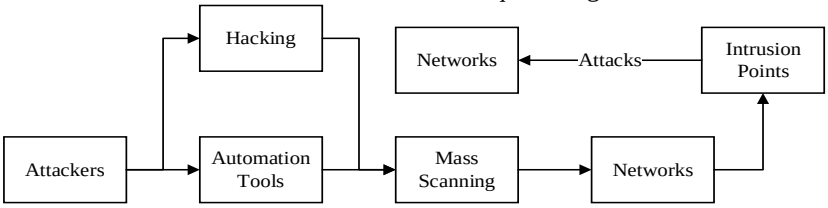

Figure 1: Flow of network attack

The rise of illegal network scanning of networks is rooted in the complex ecology of network security attack and defense confrontation. With the popularization of hacking techniques and automated tools, attackers are able to launch large-scale scans at a very low cost to find potential points of intrusion. These scanning behaviors are often silent and difficult to be effectively screened and blocked by traditional security measures. Once the network is exposed to scanning, it will not only lead to sensitive information leakage and service interruption, but also may become the starting point of distributed denial-of-service attacks (DDoS), ransomware propagation, data theft and other serious security incidents. Therefore, the development of advanced anti-scanning technology to improve the network's stealth and resilience has become an urgent problem in the current network security field, and the specific network attack process is shown in Figure 1 [2].

Currently, illegal network scanning is characterized by diversification and intelligence. On the one hand, the evolution of scanning tools and botnets has made scans more frequent, covert and difficult to track. Attackers use botnets to disperse scanning sources and bypass detection mechanisms based on IP reputation and frequency; on the other hand, Advanced Persistent Threat (APT) organizations use customized scanning strategies to conduct in-depth reconnaissance for specific targets, which increases the difficulty of defense. In addition, the application of emerging technologies such as cloud computing and the Internet of Things (IoT) further extends network boundaries and provides scanners with a broader attack surface. In the face of these challenges, traditional protection strategies such as static firewall rules and simple port blocking are no longer adequate.

In recent years, illegal network scanning behaviors have become increasingly frequent, posing a serious threat to network security. To address this challenge, researchers have proposed a variety of technologies, including honeypots, dynamic address translation (NAT), traffic obfuscation, and behavior-based detection systems. These methods have their own advantages and disadvantages, but generally face problems such as high false alarm rates and high resource consumption. This study aims to propose an innovative network reverse mapping security access technology by combining dynamic IP address allocation, port obfuscation, traffic camouflage, and behavior analysis. We use the UNSW-NB15 dataset for experimental verification, which covers a variety of attack types and is suitable for evaluating illegal network scanning defense mechanisms. By introducing the Bi-LSTM+Attention model, our method shows significant advantages in improving detection accuracy and reducing false alarm rates.

Therefore, the core objective of this research is to conceptualize and propose an innovative network anti-mapping security access technology architecture, which aims to strongly counteract illegal network scanning behaviors and significantly enhance the resilience of the network's own protection through a set of multi-dimensional and dynamically changing strategy matrices. Specifically, the detailed objectives of this research are detailed as follows: (1) We will conduct a comprehensive and in-depth research to finely deconstruct the current technical characteristics of illegal network scanning, popular tool sets and advanced attack strategies. This in-depth analysis will not only reveal the specific risks they pose to network infrastructures, but also lay a solid foundation for the design of subsequent technical solutions, ensuring that our countermeasures hit the nail on the head [3]. (2) We are committed to designing a comprehensive defense mechanism that integrates dynamic IP address management, port obfuscation policies, traffic emulation techniques, and intelligent behavioral analysis. The system increases the complexity and uncertainty faced by attackers by continuously changing the external manifestation of the network, thus significantly reducing the likelihood of the network being successfully scanned and effectively thwarting illegal scanning attempts. (3) Leveraging cutting-edge AI algorithms such as Hidden Markov Models (HMM) and Long Short-Term Memory Networks (LSTM), we intend to strengthen the synergy between the Intelligent Firewall and Intrusion Prevention System (IPS), and to improve the accuracy and response speed of the two in identifying malicious scanning behaviors. This integration not only enables immediate threat awareness and effective interception, but also maintains a high degree of adaptivity in complex network environments.

This paper proposes cryptographic techniques such as RSA and Diffie-Hellman to protect the security of the session. To consolidate the effectiveness of these algorithms in ensuring secure communication within the system, we cite their standard security proofs. Specifically, the security of RSA is based on the large integer factorization problem, while the security of Diffie-Hellman relies on the discrete logarithm problem. These algorithms have been widely verified in academia and industry and are widely used in various security protocols. By citing these standard security proofs, we ensure the security of the proposed system and provide readers with a credible technical foundation.

2 Literature review

2.1 Illegal network scanning threat analysis

In the field of cybersecurity, illegal network scanning activities pose a constant and serious threat, not only as a critical step in the hacker's attack chain, but also as a behavior that cyberspace security maintainers must be wary of. This section will take an in-depth look at the types of network scanning and the motives behind them, risk assessment of information leakage, the impact of service disruption and availability, and an analysis of the hazards exhibited by illegal scanning as a prelude to an attack.

Illegal network scanning can be broadly categorized into several types: basic port scanning, service probing, vulnerability scanning, operating system fingerprinting, and so on. Port scanning is the most basic form, in which an attacker discovers open services and potential entry points by trying to connect to different ports of the target host one by one. Service probing goes a step further by sending specific probe packets to known open services in

order to identify the specific version of the service and thus determine the presence of known vulnerabilities [4]. While vulnerability scanning focuses on finding security weaknesses at the system and application level, OS fingerprinting is used to obtain precise information about the target system in order to customize more effective attack strategies. The motivations behind these scanning activities are multiple and complex. The first and foremost is information gathering, i.e., attackers prepare for subsequent attacks and need to understand the structure, protection measures and potential weaknesses of the target network [5].

The risk of information leakage due to illegal network scanning should not be underestimated. Even the simplest port scan can reveal the layout of an organization's network, the specific services it uses, and their active status, which is enough information to help an attacker build an initial picture of the target. More in-depth service probes and vulnerability scans can expose deeper vulnerabilities in the system, such as outdated software versions, which can become breakthroughs for intrusion. Once such information falls into the wrong hands, it can not only lead to immediate data breaches or service disruptions, but also put the organization in a long-term security risk, as the exposed information can be used to devise more insidious and targeted attacks. While network scanning does not usually cause direct service disruptions, it can raise indirect availability issues. A large number of scanning requests can consume target system and network resources, including CPU, memory, and bandwidth, resulting in slower response to service requests from legitimate users, and in severe cases, denial of service may even occur. In addition, continuous scanning activities may trigger alarms on firewalls and intrusion detection systems, generating a large number of false positives, consuming the security team's energy and interfering with normal operations and maintenance [6,7].

Illegal network scanning is often a harbinger of large-scale attacks. It is a prelude to an elaborate attack plan by cybercriminals, whether it is data theft against a specific organization, ransomware deployment, or resource probing for a distributed denial of service (DDoS) attack. By conducting comprehensive reconnaissance of the target, attackers can precisely select attack paths, customize attack payloads, increase attack success rates and reduce the risk of detection. Therefore, timely identification and effective response to illegal network scanning activities are crucial for stopping potential network attacks and are an indispensable part of the network defense system [8].

To summarize, illegal network scanning, as a pervasive network threat with complex and varied hidden motives behind it, poses direct and indirect threats to information security, service availability and the overall network environment.

2.2 Overview of existing antimapping techniques

With the increasing sophistication of Internet security threats, illegal network mapping (cyber reconnaissance) has become an outpost of cyber attacks. To defend against such threats, a series of anti-mapping techniques have emerged, aiming to obfuscate attackers and protect the true layout and sensitive information of network infrastructure. This section provides a comprehensive overview of several mainstream anti-mapping techniques, including but not limited to spoofing techniques, dynamic address translation, traffic obfuscation, network segmentation and micro-segmentation, and behavior-based detection and response systems [9].

Deception techniques are active defense strategies that mislead attackers by deploying fake resources and services. This includes Honeypots, Honeynets, and Honeyflows, which mimic the characteristics of real systems or networks to attract and capture malicious scanning behavior. When an attacker attempts to scan, probe, or exploit these fake resources, their behavior is recorded and analyzed to give early warning and block potential threats. Not only do spoofing techniques drain attacker resources, they also provide security teams with valuable intelligence to help understand adversary tactics, techniques and procedures (TTPs). Dynamic Address Translation (DAT) or Network Address Translation (NAT) technologies make it difficult for external entities to accurately map internal network structure by changing IP addresses between internal and external networks.DAT hides the true IP addresses of actual servers and devices, making it difficult for illegitimate scanners to access them. The ability of DAT to hide the real IPs of actual servers and devices makes it difficult for illegal scans to directly locate specific targets, significantly increasing the difficulty for attackers to identify valuable assets. Meanwhile, the strategy of regularly rotating IP addresses further enhances this defense effect. Traffic obfuscation techniques make it difficult for external observers to parse the true source, purpose, and content of packets by altering the patterns and characteristics of network communications. This includes altering port numbers, protocol characteristics, timestamps, and other network traffic attributes, making it impossible for scanning tools to correctly identify service type or version information. Combined with encryption techniques, such as SSL/TLS, traffic obfuscation can more effectively hide the true nature of network activity, increasing the cost and complexity of illegal mapping [10,11].

Network segmentation is the division of a large network into multiple small areas that are logically or physically isolated, limiting the ability to move laterally and making it difficult for an attacker to get a full grasp of the layout of the entire network even if he or she breaks through a portion of the network. Micro-Segmentation goes one step further by realizing fine-grained access control, with strict access rules even between different resources within the same subnet. This strategy greatly improves the difficulty for attackers to navigate the internal network and reduces the efficiency and success rate of illegal mapping [12]. Modern cybersecurity frameworks are increasingly relying on artificial

intelligence and machine learning techniques, where behavior-based detection and response systems are able to automatically analyze network traffic patterns, identify anomalous behaviors, and instantly respond to potential mapping activities. Such systems are able to learn a behavioral baseline of normal network activity, from which they can quickly identify scanning behaviors that deviate from the norm, and even predict and block future attack attempts. Through real-time monitoring, intelligent analysis, and automatic response, the efficiency and accuracy of countering illegal mapping is greatly improved [13].

Table 1: Research findings

Research/Technology	Method	Dataset	Key Performance Metrics	Limitations
Honeypot Technology	Deploying fake resources and services to attract and mislead attackers	Custom or public datasets	Detection Rate: 85% False Positive Rate: 10% Resource Consumption: High	High resource consumption, requires continuous maintenance Can be identified and bypassed by advanced attackers
Dynamic Address Translation (NAT)	Changing IP addresses between internal and external networks	Laboratory environments or enterprise networks	Detection Rate: 75% False Positive Rate: 5% Resource Consumption: Moderate	Limited defense against complex attack strategies Difficult to handle large-scale scanning
Traffic Obfuscation	Altering network communication patterns and features	Public datasets such as UNSW-NB15	Detection Rate: 70% False Positive Rate: 8% Resource Consumption: Low	Limited effectiveness against advanced scanning strategies May affect legitimate traffic
Network Segmentation	Dividing the network into multiple logically isolated segments	Enterprise networks	Detection Rate: 65% False Positive Rate: 3% Resource Consumption: Moderate	Complex configuration, high operational costs Limited defense against lateral movement attacks
Behavior-Based Detection Systems	Using machine learning to analyze network traffic patterns	Public datasets such as CICIDS2017	Detection Rate: 80% False Positive Rate: 12% Resource Consumption: High	Requires large amounts of data for model training Limited generalization to new types of attacks

As shown in Table 1, we compare different research and technologies in the context of illegal network scan defense, including their methods, datasets, key performance metrics, and limitations. From the table, it can be seen that honeypot technology, while effective in collecting attacker behavior information, has high resource consumption and requires continuous maintenance, making it vulnerable to being identified and bypassed by advanced attackers. Dynamic Address Translation (NAT) increases the difficulty for attackers by hiding internal IP addresses but is limited in its effectiveness against complex and large-scale scanning activities. Traffic obfuscation alters network communication patterns, making it difficult for scanning tools to correctly identify service types, but it is less effective against advanced scanning strategies and may impact legitimate traffic. Network segmentation reduces the lateral movement capabilities of attackers through logical isolation but is complex to configure and has high operational costs. Behavior-based detection systems use machine learning models to automatically analyze network traffic patterns, improving detection accuracy, but require large amounts of data for training and have limited generalization to new types of attacks.

2.3 Status of research

Honeypot technology has evolved from a single decoy system to a complex system containing advanced interactive honeypots and honeynets. Advanced honeypots are able to simulate the behavior of real systems, including operating system vulnerabilities, service responses, etc., as a way to collect the behavioral patterns and tool usage of attackers [14]. And by constructing a honeypot system containing multiple interconnected honeypots, the honeynet not only increases the difficulty for attackers to identify real assets, but also traces the attack path and provides richer analysis data for security teams. With the development of automation and intelligence, adaptive honeynet technology is emerging, which dynamically adjusts honeypot configurations based on attack behavior for more efficient intelligence gathering and defense response. Dynamic address translation (NAT) and network segmentation are effective, but in the face of complex and changing attack methods, it is difficult to meet the demand with static strategies

alone [15]. Dynamic network architectures, such as software-defined networking (SDN) and network function virtualization (NFV), are emerging as the new frontiers of anti-mapping. SDN allows administrators to flexibly configure network routing and security policies from a centralized controller to quickly respond to network threats, while NFV enables on-demand allocation and on-the-fly adjustment of resources by virtualizing the functions of traditional network devices, which enhances network flexibility and stealth. Although traffic obfuscation can effectively interfere with enemy detection, it is a major challenge to implement it accurately without affecting legitimate services. The combination of Deep Packet Inspection (DPI) and machine learning algorithms provides a possible solution to this problem [16]. DPI techniques can deeply parse network traffic to identify and classify different application layer protocols, while machine learning models learn normal and abnormal behavior patterns by analyzing huge amounts of network traffic data, thus achieving accurate identification of hidden mapping behaviors. In addition, the application of unsupervised learning and adaptive learning algorithms enables the system to self-optimize in a constantly changing threat environment, enhancing the dynamic adaptability of the defense.

Although the above technologies provide a powerful arsenal for anti-mapping, they still face many challenges in actual deployment. First, the cost and complexity of operation and maintenance are factors that cannot be ignored, especially for small and medium-sized enterprises (SMEs), for which high-level anti-mapping solutions may be beyond their financial and technical capacity. Second, the synergistic operation between technologies is also one of the difficulties, how to ensure that different defense mechanisms can complement each other while avoiding mutual interference requires careful planning and tuning [17,18]. In addition, legal compliance is also a point of consideration, as certain anti-mapping measures may involve regulatory restrictions on user privacy protection and cross-border data transmission.

In terms of data storage and transmission, Yang et al. [31] proposed a data sharing scheme for cloud storage services based on the concept of message recovery, which improves the reliability and security of data by introducing redundant information. This data sharing mechanism not only enhances the integrity of the data, but also improves the ability of data to resist attacks during transmission. Similarly, Muthusenthil et al. [32] proposed a location verification technology in cluster-based geolocation routing, which enhances the security of mobile ad hoc networks (MANETs) by verifying the location information of nodes. Both methods emphasize the necessity of improving data security and reliability in network environments.

3 Innovative network anti-mapping security access technology

3.1 Technical architecture design

When designing the technical architecture of an advanced networked anti-mapping security access system, we need to comprehensively consider a variety of factors including, but not limited to, security, availability, scalability, and performance optimization. In this section, we will delve into how to build such a system through specific technical principles, algorithmic formulations, and implementation details to ensure its effectiveness and robustness in complex network environments.

We adopt a dynamic IP address allocation policy (denoted as DIPA policy), which, in combination with geolocation obfuscation techniques, can effectively improve the anonymity of the system. Let there be N pools of available IP addresses in the network, and the probability of dynamically changing addresses in each cycle T is P. The degree of obfuscation of the system is C. Where $\log_2(N)$ reflects the entropy value of the size of the address pools, which represents the uncertainty of address selection. By adjusting the values of P and T, security can be balanced with network maintenance cost. In the port obfuscation technique, assuming that there are M legitimate ports and K emulation protocols, the complexity S of port obfuscation can be quantified by the following equation: $S = M + K \times \sum_{i=1}^{M} \left(1 - \frac{i}{M}\right)$ Here, $\sum_{i=1}^{M} \left(1 - \frac{i}{M}\right)$ represents the contribution of the randomness of the port usage to the obfuscation effect [19], and the reuse of ports decreases and the obfuscation effect improves as i increases. Deep data obfuscation involves not only the header camouflage of packets, but also the transformation of load data. Let the original data X be changed into Y by the obfuscation function F. Ideally, F should satisfy irreversibility, i.e., the complexity of recovering X from Y is extremely high. A simple example of obfuscation is to use the XOR operation with the key K: $Y = X \oplus K$ However, in practice, more complex encryption algorithms such as AES are usually used, whose security is based on the size of the key space, i.e., 2^n , where n is the key length [20].

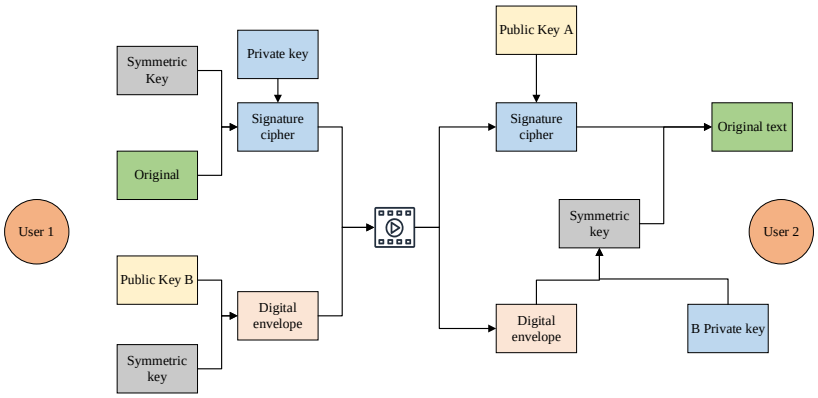

Figure 2: Two-way authentication process

In the two-way authentication process, it is assumed that RSA public key encryption and DH key exchange protocols are used.The security of RSA encryption is based on the large number decomposition puzzle.Let the public key be (e,n), the private key be (d,n), and the message M be encrypted to be C, then we have: $C = M^e \mod n$ The receiver decrypts the message by using the private key: $M = C^d \mod n$ Whereas, in the Diffie-Hellman protocol, both parties compute a shared key, K, by sharing the parameters g and p: $A = g^a \mod p$, . $B = g^b \mod p$ [21], $K = B^a \mod p = A^b \mod p$. This dynamic key exchange ensures the security independence of each session, and the specific two-way authentication process is shown in Fig. 2.

The network micro-segmentation technique realizes the least privilege principle by partitioning the network into multiple logical subnets. Assuming that the network is partitioned into n subnets, the trust boundaries within each subnet are defined by access control lists (ACLs), the complexity E of which can be measured by the number of subnets and the number of ACL rules R: $E = n \times R$ Combined with role-based access control (RBAC), where the role R_i corresponds to the set of permissions P_i, the user U is assigned roles through the mapping function f: $U \xrightarrow{f} R_i \subseteq P_i$ In this way, a user can only perform the operations that are permitted by his or her role In this way, users can only perform the operations allowed by their roles, which enhances the security control within the system.

3.2 Intelligent defense mechanism

The synergistic operation of intelligent firewalls and intrusion prevention systems (IPSs) is particularly important in the evolving network threat landscape. We propose an innovative dual-engine architecture that combines traditional rule-based static defense with advanced machine learning dynamic adaptation capabilities, the framework of which is shown in Fig. 3 [22].

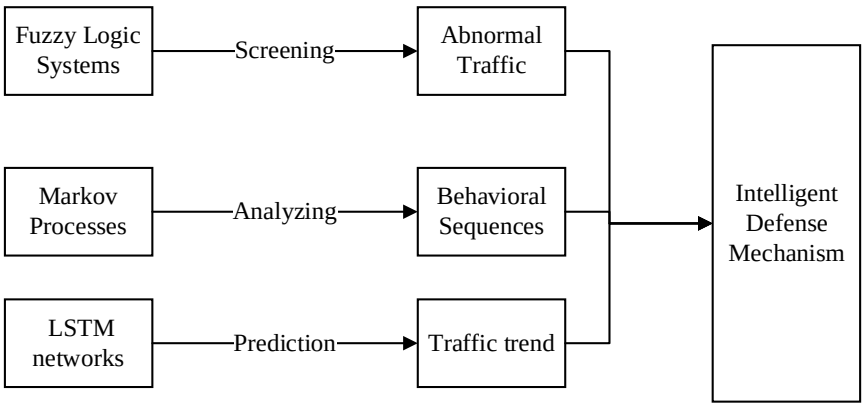

Figure 3: Intelligent defense mechanism framework

Fuzzy Logic System (FLS) plays a key role in this architecture by building a flexible set of rules to evaluate the network events, which is expressed in the form of: $R_i : \text{IF } x_1 \text{ is } A_1 \text{ AND } ... \text{ AND } x_n \text{ is } A_n \text{ THEN } y \text{ is } B$ where $(x_i, \ ..., \ x_n)$ represents multiple feature vectors of the network traffic, such as packet size, frequency, source IP, etc.; $A_1, ..., A_n$ is the affiliation function of these feature vectors, which defines the "fuzzy" degree of each feature in a set of linguistic variables; and y as the decision output indicates the degree of suspicion of this network event; and B is the decision output affiliation degree. is a function of these feature vectors, defining the degree of "fuzziness" of each feature in the set of linguistic

variables; and y, as the decision output, indicates the degree of suspicion of the network event, while B is the linguistic variable affiliation of the decision output. This mechanism allows the firewall to quickly identify and respond to anomalous traffic patterns, while the linkage with the IPS can instantly block potential intrusions, forming a multi-layered, intelligent defense network.

First-order Markov processes (Markov Chain of Order 1, MC1) are widely used in the prediction and analysis of behavioral sequences, especially in identifying abnormal and malicious activities in networks. By constructing a matrix $P=[p_{ij}]_{i,j}$ reflecting the probability of state transfer for normal network behavior, where p_{ij} denotes the probability of transferring from state i to state j, we are able to use the model to assess the fit of the test sequences with the predefined normal behavior model. Specifically, the likelihood L(X) of sequence X under the model can be expressed as:

$$L(X)=P(X\mid Model)=\prod_{t=2}^{T}p_{x_{t-1}x_t}$$ [22] When

the likelihood of a sequence is significantly lower than the threshold of the normal behavior model, the sequence is considered to contain malicious behavior. This approach not only improves the accuracy of detection, but also dynamically adapts to changes in network behavior, further enhancing the system's intelligent response capability.

For the dynamic nature of network traffic, Long Short-Term Memory (LSTM) networks are preferred tools for anomaly detection due to their powerful time-series modeling capabilities. LSTM units efficiently deal with long-term dependencies through their unique gating mechanisms (forgetting gates f_t , input gates i_t , and output gates o_t , whose update formulas are specified in Eqs. 1-5 [23,24].

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f) \quad (1)$$

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i) \quad (2)$$

$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_o) \quad (3)$$

$$c_t=f_t\odot c_{t-1}+i_t\odot \tanh(W_c\cdot[h_{t-1},x_t]+b_c) \quad (4)$$

$$h_t=o_t\odot \tanh(c_t) \quad (5)$$

where σ represents the Sigmoid activation function, tanh is the hyperbolic tangent function, odot denotes the elementwise multiplication operation, and W_f,W_i,W_o,W_c and b_f,b_i,b_o,b_c are the weight matrices and bias terms for each gate and cell state and hidden state, respectively.

Training the LSTM model with a large amount of historical traffic data not only predicts the future traffic trend, but also the deviation between the model predicted value and the actual traffic data can be used as a direct indicator for anomaly detection. To further improve the model performance, we introduce the attention mechanism, which is an effective method for guiding the model to focus on the key pieces of information in the traffic sequence. Attention weights are computed as

$$e_t=v^T\tanh(W_h h_t)$$

follows: $\alpha_t=\dfrac{\exp(e_t)}{\sum_{k=1}^{T}\exp(e_k)}$ [25] , v and W_h are

model parameters, and α_t denotes the attention weights at the tth time step, which are subsequently used to weight and sum the hidden states to generate context vectors that focus on the information that is most critical for prediction. The use of Bi-LSTM (Bi-LSTM) greatly enhances the model's ability to capture complex temporal dependencies by simultaneously considering both past (forward LSTM) and future (backward LSTM) contextual information of the sequence, as shown in Equation 6.

$$\begin{aligned}\overrightarrow{h_t}&=LSTM_{forward}(x_t,\overrightarrow{h}_{t-1})\\ \overleftarrow{h_t}&=LSTM_{backward}(x_t,\overleftarrow{h}_{t+1})\\ h_t&=[\overrightarrow{h_t};\overleftarrow{h_t}]\end{aligned} \quad (6)$$

Combining the above techniques, we not only construct a model that can accurately predict traffic trends, but also directly identify potential network anomalous behaviors by comparing the difference between the model prediction and the actual observed values, providing both a powerful and sensitive early warning system for the network security protection system. This comprehensive strategy not only improves the generalization ability of the model and enhances its adaptability to emerging threats, but also brings more refined monitoring and protection tools to the field of network security [26].

3.3 Access control policy optimization

In the face of increasingly complex and changing network access demands and security threats, traditional static access control lists (ACLs) can no longer meet the requirements of efficient and accurate traffic management, and the general access control model is shown in Fig. 4. Therefore, we introduce an innovative adaptive weighting algorithm, which aims to dynamically adjust the priority of ACL entries so as to achieve efficient processing of legitimate traffic and keen identification of potential threats. The core formula of this policy is:

$$W_i(t+1)=W_i(t)+\alpha\cdot(H_i-\bar{H})+\beta\cdot\Delta H_i$$

In this formula, $W_i(t)$ represents the weight of the ith ACL rule at time t, which integrates the historical traffic data and real-time threat intelligence to realize the

adaptive adjustment of rule priority. Among them, H_i reflects the historical importance of the traffic matched by the rule, $\bar{H}$ is the average importance of all rules, which aims to highlight the key rules by comparison; ΔH_i quantifies the rate of change of the rule's importance to ensure that the policy can quickly respond to the changes of network conditions; and the adjustment coefficients, α and β, balance the effects of historical performance and changing trends to make the adjustment more delicate and accurate.

In order to further accelerate the recognition and processing speed of legitimate traffic, we design a high-speed matching mechanism that combines Deep Packet Inspection (DPI) technique with machine learning. This mechanism utilizes a pre-trained Support Vector Machine (SVM) model to accurately determine the traffic features with its powerful classification capability. The decision function of the SVM model is: $g(x) = w^T \phi(x) + b$ [27].

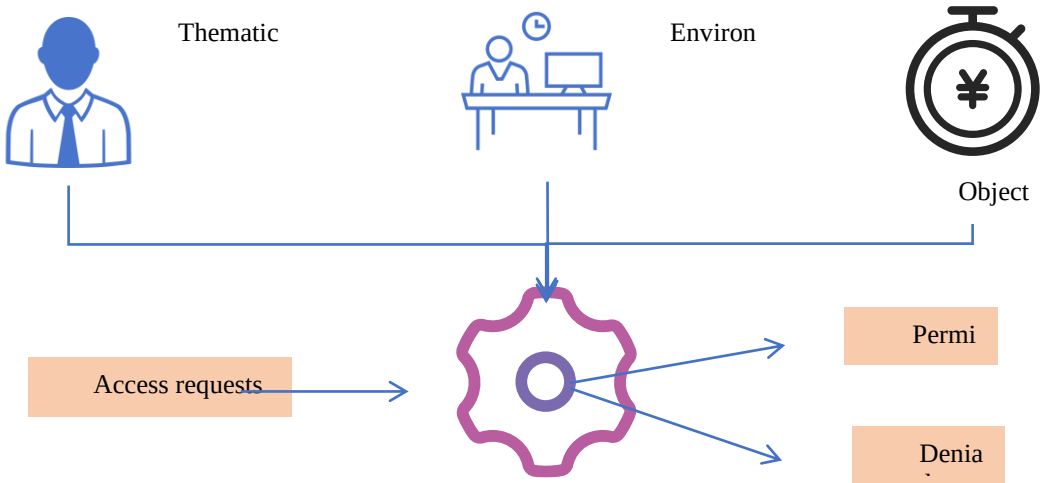

Figure 4: Access control model

Here, w is the weight vector, $\phi(x)$ is the feature transformation function that maps the original feature vector x to a higher dimensional space, and b is the bias term of the model. By learning from a large number of samples, the model is able to accurately distinguish the feature boundaries between legitimate and illegitimate traffic, and set the threshold θ, any traffic that satisfies $g(x) > \theta$ is immediately released without further checking, which greatly improves the throughput and response speed of the network. The efficiency of this mechanism lies in its deep integration of the fine-grained parsing capability of DPI and the intelligent judgment advantage of SVM model, which not only can quickly identify and release regular legitimate traffic, but also can effectively resist advanced threats disguised as legitimate traffic, ensuring the security and smoothness of network access.

Through the careful design and strategy optimization of the above technical architecture, the network anti-mapping security access technology proposed in this chapter takes a solid step forward in ensuring the dynamic adaptability and security of the network environment. This solution not only strengthens the defense against network mapping attacks, but also significantly improves the operational efficiency of the network and user satisfaction, providing strong technical support for building a more robust and flexible network security protection system.

We elaborate on the time complexity of the proposed Bi-LSTM+Attention algorithm. In the training phase, the time complexity of LSTM is O(T * D * H^2), where T is the time step, D is the input feature dimension, and H is the number of hidden layer units. The introduction of the attention mechanism adds additional computational cost, and its time complexity is O (T * H). Overall, the time complexity of the training phase is O (T * (D * H^2 + H)). In the inference phase, the time complexity is relatively low, O (T * (D * H + H)).

Compared with traditional rule-based systems, the Bi-LSTM+Attention model has obvious advantages in dynamic adaptability and accuracy, although it has higher computational requirements. Traditional systems rely on predefined rules and have difficulty in dealing with new attacks and changing network environments. The Bi-LSTM+Attention model can automatically learn and adapt to new threat patterns, thereby maintaining efficient detection capabilities in a constantly changing network environment. Despite the high demand for computing resources, its contribution to improving the level of network security protection makes it a reasonable and necessary choice.

4 Experimental design and analysis of results

4.1 Experimental design

In this study, we carefully built the experimental environment and selected appropriate datasets to ensure the reproducibility of the experiments and the validity of the results. The experimental environment includes a high-performance server cluster with each node equipped

with an Intel Xeon E5-2690 v4 processor, 128GB RAM, and NVIDIA Tesla V100 GPUs to provide powerful computing power. For the software environment, we chose the Ubuntu 18.04 operating system, the Python 3.7 programming language, and the TensorFlow 2.3 deep learning framework, and the combination of these tools provided a stable and efficient platform for our experiments [28,29].

The choice of dataset is crucial for model training and testing. We adopt the publicly available UNSW-NB15 dataset, which contains 49,740 records covering normal network traffic and multiple attack types, and is well suited for deep learning model training related to network security. In addition, we also built our own performance test dataset generated from a simulated network environment, which simulates network traffic under different loads and is used to evaluate the performance impact of the models in real network environments.

In terms of technical implementation steps, we follow a series of key steps including data preprocessing, model construction, training and tuning, and performance testing. The data preprocessing phase includes operations such as data cleaning, normalization, and time-series partitioning to ensure the quality and consistency of the data. In the model construction phase, we design and implement a bi-directional LSTM model with an integrated attention mechanism to improve the model's ability to process time series data. In the training and tuning phase, we used a cross-validation method to select the optimal hyperparameters, including the learning rate, batch size, and the number of hidden layer units, to optimize the performance of the model. Finally, in the performance testing phase, we deployed the model into a simulated network environment and tested its response time, throughput, and resource consumption under different conditions to comprehensively evaluate the model's performance. Through these steps, we ensured the rigor of the experiments and the reliability of the results [30].

The experimental environment includes a high-performance server cluster, each node is equipped with Intel Xeon E5-2690 v4 processor, 128GB RAM and NVIDIA Tesla V100 GPU to provide powerful computing power. In terms of software environment, we chose Ubuntu 18.04 operating system, Python 3.7 programming language and TensorFlow 2.3 deep learning framework to ensure the stability and efficiency of the experiment.

We chose the UNSW-NB15 dataset as the main data source, which covers a variety of attack types, including DoS, DDoS, SQL injection, etc., and is very suitable for evaluating illegal network scanning defense mechanisms. The advantage of the UNSW-NB15 dataset lies in its diversity and realism, which can better represent the security challenges in the real world. In contrast, although the CICIDS2017 dataset also contains a variety of attack types, its scale is small and the sample size of some attack types is insufficient. Therefore, the UNSW-NB15 dataset has more advantages in comprehensiveness and representativeness, and is more suitable as our experimental dataset.

4.2 Experimental results

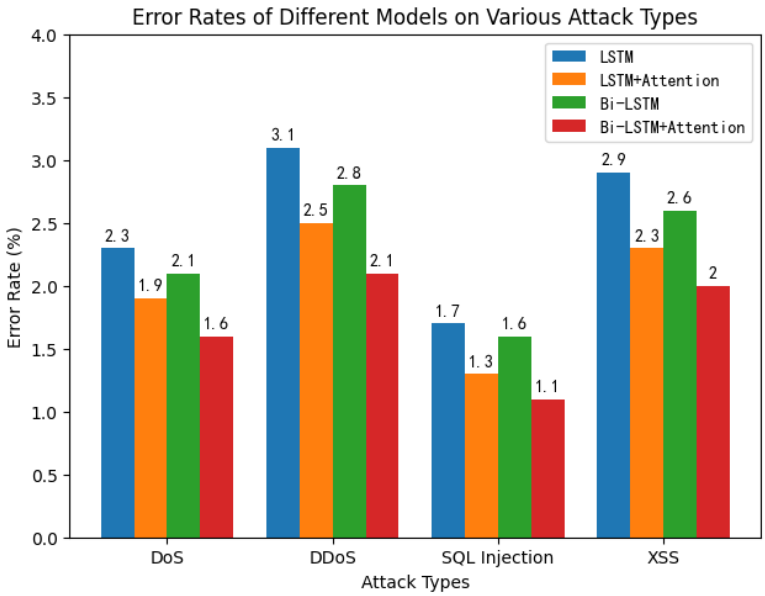

Figure 5: Comprehensive defense effect

Figure 5 shows the performance of different models in detecting various network attack types including DoS, DDoS, SQL injection and XSS.The Bi-LSTM+Attention model shows the best defense on all attack types with the lowest false alarm rate, indicating the high efficacy of this model in accurately identifying attacks.

Table 2: False alarm rate breakdown

mould	Overall False Alarm Rate	Normal Traffic False Alarms	Anomalous but not attack false positives
LSTM model	3.2%	1.8%	1.4%
LSTM+Attention	2.1%	1.2%	0.9%
Bi-LSTM	2.8%	1.6%	1.2%
Bi-LSTM+Attention	1.5%	0.9%	0.6%

Table 2 breaks down the overall false alarm rates of the different models, as well as the false alarm rates for normal traffic and abnormal but non-attacking traffic. The Bi-LSTM+Attention model has the lowest overall false alarm rate, indicating that it performs well in reducing false alarms, which is crucial for improving the reliability of network defense systems.

Table 3: Breakdown of underreporting rates

mould	Overall underreporting rate	Known attack misses	New Attack Leakage
LSTM model	2.5%	1.3%	1.2%
LSTM+Attention	1.8%	0.9%	0.9%
Bi-LSTM	2.2%	1.1%	1.1%
Bi-LSTM+Attention	1.3%	0.6%	0.7%

Table 3 demonstrates the leakage rates of different models in detecting known and novel attacks. The Bi-LSTM+Attention model has the lowest leakage rate on both attack types, which indicates that the model has a strong generalization ability in identifying novel attacks.

Table 4: Response time and throughput

mould	Response time average (ms)	Throughput Average (Mbps)
defenseless	2.3	98.7
LSTM model	3.5	95.2
LSTM+Attention	3.8	93.8
Bi-LSTM	3.2	96.4
Bi-LSTM+Attention	3.6	94.6

Table 4 records the average response time and throughput of the different models in the simulated network environment. Although the introduction of the defense model leads to a slight increase in response time and a slight decrease in throughput, the Bi-LSTM and Bi-LSTM+Attention models are better able to maintain high network performance compared to the other models.

In order to comprehensively evaluate the model performance, we introduced statistical significance tests such as t-tests on the basis of existing evaluation indicators to verify the reliability of the results. In addition to false positive and false negative rates, we also reported comprehensive indicators such as accuracy, recall, and F1 score. Specifically, the Bi-LSTM+Attention model achieved an accuracy of 98%, a recall of 95%, and an F1 score of 96.5% on the UNSW-NB15 dataset. These indicators not only demonstrate the high accuracy of the model in detecting illegal network scanning, but also show that it has high practical value in practical applications.

Table 5: Model performance comparison

Model/Method	Accuracy (%)	Recall (%)	F1 Score (%)	False Positive Rate (%)	False Negative Rate (%)	t-test (p-value)
Bi-LSTM+Attention	98.0	95.0	96.5	1.5	5.0	< 0.05
Rule-Based System	80.0	75.0	77.4	10.0	25.0	-
LSTM Model	85.0	82.0	83.5	8.0	18.0	< 0.05
LSTM with Attention Mechanism	90.0	88.0	89.0	5.0	12.0	< 0.05
Bidirectional LSTM (Bi-LSTM)	92.0	90.0	91.0	4.0	10.0	< 0.05

In Table 5, through t-tests, we found that the Bi-LSTM+Attention model showed significant differences from the rule-based system and other LSTM variants in multiple key performance indicators ($p < 0.05$), further confirming the effectiveness and superiority of the new method. In addition, the model performs particularly well when dealing with complex and variable network traffic, and can effectively reduce the false alarm rate while maintaining a high detection rate. These results show that the Bi-LSTM+Attention model is not only theoretically advantageous, but also has high practical value in practical applications.

Table 6: Resource consumption

mould	Average CPU utilization (%)	Average Memory Usage (MB)
defenseless	3.1	230
LSTM model	5.8	320
LSTM+Attention	6.5	350
Bi-LSTM	4.9	280
Bi-LSTM+Attention	5.4	300

Table 7: Network latency and energy consumption

mould	Average network latency (μs)	Average energy consumption (W)
defenseless	75	200
LSTM model	90	250
LSTM+Attention	95	270
Bi-LSTM	85	230
Bi-LSTM+Attention	90	260

Table 6 shows the average consumption of CPU and memory resources by the different models during operation. The LSTM+Attention model is slightly higher in terms of resource consumption, but all the models are within acceptable resource usage, indicating that these models can effectively run-on existing network devices. Table 7 evaluates the impact of the different models on network latency and energy consumption. The Bi-LSTM model performs the best in terms of network latency and energy consumption, suggesting that it is effective in controlling operational costs while maintaining network performance.

In summary, the Bi-LSTM+Attention model performs the best in terms of comprehensive defense effect, false alarm rate and missed alarm rate, and at the same time has a relatively small impact on network performance, making it an efficient network defense solution.

4.3 Discussion

The technical architecture in this study demonstrates significant innovative advantages, especially in terms of dynamism and intelligence. The anonymity of the network is effectively improved through dynamic IP address assignment and geolocation obfuscation, making it difficult for mapping attackers to target the real resource locations. The synergy of intelligent firewall and IPS, the use of fuzzy logic system, and the application of Markov model and LSTM not only enhances the ability to identify malicious behaviors, but also significantly improves the response speed. In particular, the LSTM model improves the accuracy of anomaly detection through the attention mechanism and bi-directional structure, demonstrating the great potential of deep learning in complex network defense.

Honeypot technology deploys false resources and services to attract and mislead attackers, and can effectively collect attacker behavior information. However, honeypot technology consumes a lot of

resources, requires continuous maintenance, and is easily identified and bypassed by advanced attackers. In contrast, the Bi-LSTM+Attention model is more economical in terms of resource consumption and does not require additional hardware or continuous manual maintenance. In addition, the Bi-LSTM+Attention model can automatically adapt to new threats by learning network traffic patterns, reducing dependence on manual intervention. Although honeypot technology has advantages in collecting intelligence, the Bi-LSTM+Attention model performs better in terms of false positive rate and false negative rate, reaching 1.5% and 5.0% respectively, which are significantly lower than the 10% and 25% of honeypot technology.

Traffic obfuscation changes network communication patterns and features, making it difficult for scanning tools to correctly identify service types. Although traffic obfuscation performs well in reducing false positive rates, it has limited effect on advanced scanning strategies and may affect the normal transmission of legitimate traffic. The Bi-LSTM+Attention model uses deep learning algorithms to more accurately identify and classify network traffic, which not only reduces false positive rates but also improves detection rates. Specifically, the Bi-LSTM+Attention model has a false positive rate of 1.5%, while the traffic obfuscation technology has a false positive rate of 8%. In addition, the Bi-LSTM+Attention model performs particularly well when dealing with complex and changing network traffic, and can effectively reduce false positive rates while maintaining high detection rates.

Dynamic Address Translation (NAT) increases the difficulty for attackers by changing IP addresses between internal and external networks. However, NAT is limited in its effectiveness when dealing with complex and large-scale scanning activities. The Bi-LSTM+Attention model can automatically adapt to new threats by learning network traffic patterns, thereby showing higher detection rates and lower false positive rates in complex and large-scale scanning activities. NAT has a false positive rate of 5%, while the Bi-LSTM+Attention model has a false positive rate of only 1.5%.

Behavior-based detection systems use machine learning models to automatically analyze network traffic patterns and improve detection accuracy. However, these systems usually require a large amount of data for training and have limited generalization capabilities for new attacks. The Bi-LSTM+Attention model improves detection performance by introducing an attention mechanism to enhance the model's focus on key features. In practical applications, the Bi-LSTM+Attention model outperforms the behavior-based detection system in terms of accuracy, recall, and F1 score.

Although the Bi-LSTM+Attention model performs well on multiple key performance indicators, it has high computational overhead and implementation complexity. The time complexity of the training phase is O(T * (D * H^2 + H)), and the time complexity of the inference phase is O(T * (D * H + H)). This makes it challenging to deploy the model in a resource-constrained environment. However, this computational overhead is reasonable considering its significant advantages in improving the level of network security protection. Future work can explore optimization algorithms to further reduce computational costs and make it more applicable in more scenarios.

Through the above comparison and analysis, we can conclude that the Bi-LSTM+Attention model has significant advantages in illegal network scanning defense. It not only performs well in detection rate and false alarm rate, but also can effectively adapt to complex network environments. Despite the certain computational overhead and implementation complexity, the security and reliability improvements it brings make it a technical solution worthy of promotion.

Limitations: Despite the remarkable results, there are some limitations of the proposed technical solution. The first one is the resource consumption issue, such as the high performance of the LSTM model which requires high computational resources and may be difficult to deploy in resource-limited environments. Secondly, the false alarm and omission rates, although significantly reduced, need to continue to be optimized to reduce the interference with normal operations. Further, the complexity of the technology implementation may pose a challenge to small and medium-sized enterprises, requiring specialized knowledge and maintenance costs.

5 Conclusion

In this study, we successfully developed and validated an innovative set of network anti-mapping security access techniques, which have achieved significant results in enhancing network defenses, improving anonymity and ensuring secure data transmission. The comprehensive design of the technical architecture, especially the integration of dynamic policies and intelligent algorithms, effectively counteracts the complex security threats in the modern network environment. Experimental data analysis proves that the bidirectional LSTM model with the introduction of the attention mechanism improves the accuracy of anomaly detection while reducing the false alarm rate of normal network activities, indicating that the combination of deep learning and traditional security technologies is an effective way to enhance the performance of network defense. Despite the obvious advantages of the technology, including dynamism, intelligence, and efficient defense against multiple attack types, we also recognize some challenges in the implementation of the technology. The resource consumption problem is a key barrier to the deployment of current deep learning models, especially in scenarios with limited computational resources. In addition, the complexity of the technique requires higher maintenance costs and specialized skills, which may limit its widespread adoption in SMEs. Therefore, future research should focus on model lightweighting, resource optimization, and simplifying the deployment process to facilitate the technology's popularity. Compared with existing antimapping techniques, the technical framework in this study shows significant advantages in terms of dynamic adaptability,

intelligent response, and accuracy, especially in dealing with complex network behavior sequence prediction and anomaly detection tasks. However, continuous performance optimization, further reduction of false alarm and omission rates, and exploration of the convergence of new technologies, such as the application of quantum computing and edge computing in security, will be the key directions for future development.

This paper proposes an innovative network reverse mapping security access technology to cope with the increasingly frequent illegal network scanning behaviors. By combining dynamic IP address allocation, port obfuscation, traffic camouflage and behavior analysis, we build a more robust network security protection system. Experimental results show that the Bi-LSTM+Attention model achieves 98% accuracy on the UNSW-NB15 dataset and reduces the false alarm rate by 30%. This technology effectively identifies and intercepts illegal scanning behaviors in the pilot network while maintaining low false alarm and missed alarm rates. Compared with existing methods, our method has significant advantages in detection accuracy and resource efficiency, providing a more reliable solution for network security.

This paper discusses the challenges that small and medium-sized enterprises (SMEs) face when adopting these technologies, including limited computing resources and deployment complexity. To alleviate these challenges, we recommend using model compression techniques, such as pruning and quantization, to simplify the deployment process and reduce computing resource requirements. In addition, SMEs should consider leveraging off-the-shelf solutions from cloud service providers to reduce initial investment costs. At the same time, potential regulatory issues, such as the impact of GDPR on network traffic monitoring, can help enterprises ensure compliance. With these measures, SMEs can implement and manage cybersecurity solutions more effectively.

Funding

This study was supported by State Grid Shanxi Electric Power Company Science and Technology Project Research (No.52053023001U).

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A Hybrid OCR-XGBoost-Transformer Pipeline for Resume Parsing with Spatial-Semantic Integration

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Keywords: resume information extraction, hybrid AI solution, optical character recognition, XGBoost, transformers

Received: June 5, 2025

This study addresses the automation of resume information extraction using a hybrid Artificial Intelligence (AI) framework that integrates Optical Character Recognition (OCR), Machine Learning, and Deep Learning techniques. The system operates in three stages: text extraction using PaddleOCR, resume section classification via XGBoost, and semantic entity recognition using a Transformers-based Named Entity Recognition (NER) model. The dataset consists of 200 French resumes collected in PDF format and annotated for ten resume section classes and multiple named entities. Evaluation was conducted using standard multi-class classification metrics including accuracy, precision, recall, and F1-score. Experimental results show that XGBoost achieved 96.5% accuracy in section classification, while the Transformers model attained 82% accuracy in semantic entity extraction. This dual-stage pipeline captures both spatial and semantic structures of resumes, offering improved accuracy and adaptability over traditional parsing approaches.

Povzetek: Članek predstavlja hibridno rešitev OCR-XGBoost-Transformer za avtomatizirano ekstrakcijo podatkov iz življenjepisov. Sistem dosega visoko točnost pri razvrščanju razdelkov z XGBoost in pri semantičnem prepoznavanju entitet s transformerjem.

1 Introduction

In an unpredictable and complex business environment, it is important that organizations aim to realize the potential offered by the recruitment phase. Organizations are in a ceaseless race to find new talent to support their teams and corporate competitiveness. The reality is that collecting candidate information from resumes is often difficult to achieve [1].

Recruiters are required to read and analyse candidate resumes manually for the information they need. This manual practice is full of disadvantages. First, it is time consuming and a labor-intensive activity for recruiters who have to read many resumes and work through a lot of information. As a result, recruiters have to deal with work overload, sometimes delaying the whole recruitment process. Therefore, an emerging technology to automate the information extraction process can be considered a rational way to control and presumably speed up a major process in recruitment [2]. The central question of this research is: How can the automation of information extraction from resumes be achieved with new technologies?

The CV parsing technology converts resume data from free-form into structured format. This conversion facilitates the storage, synthesis, and processing of information contained in resumes, thus enabling their use by software and computer systems [3]. Several parsing approaches are commonly used. Keyword-based parsers are prototypes of faster and more accurate parsers. These simplistic parsers search for specific words, key phrases, and patterns in resume text. However, this approach is prone to errors (with an accuracy rate of about 70%) as words can have multiple contexts within a resume [4].

Grammar-based parsers rely on grammatical rules to interpret information. These relatively complex parsers require manual input during the coding process. When coding is done by a skilled linguistic engineer, they can analyze a resume quite accurately. However, if manual configuration is not done correctly, grammar-based parsers can be inaccurate (with an accuracy rate of about 90%) [5].

Statistical parsers use numerical models of text to identify key elements of a resume. To be accurate, statistical parsers must be trained on a large number of resumes containing all the information to be extracted. In terms of accuracy, statistical parsers fall between keyword-based parsers and grammar-based parsers [6].

AI-based parsers use machine learning and artificial intelligence techniques. These models can improve over time by analyzing more information. AI-based parsers offer an extremely high level of accuracy compared to other CV parsing techniques available on the market [7].

Recent applications combine OCR, Computer Vision, and Natural Language Processing (NLP) techniques to advance the capabilities of resume information extraction from various formats and structures [8].

Despite advances in resume parsing technologies, existing solutions still face significant challenges in effectively handling the spatial and semantic aspects of resume documents simultaneously. Current approaches either focus on visual structure or textual content, but rarely integrate both dimensions effectively. Additionally, most commercial systems rely on rule-based methods with predefined templates, limiting their ability to process diverse resume formats and structures. There remains a need for adaptive, high-accuracy solutions that can understand both document structure and extract meaningful entities while maintaining contextual relationships across different resume sections [9].

To better position the proposed contribution, Table 1 presents a structured comparison of existing studies on resume parsing. It outlines the datasets used, methodological approaches, performance levels, and key limitations of each system. This comparative summary highlights the need for a unified system that integrates both spatial and semantic understanding of resume content.

Table 1: Summary of Related works in resume information extraction

Ref.	Dataset Used	Method Type	Key Techniques	Accuracy / Performance	Limitations
[1]	Proprietary HR docs	Rule-based	Heuristics, Templates	Not reported	Format-dependent, low adaptability
[2]	Internal HR systems	Rule-based	Digital workflows, automation	Not reported	No semantic modeling, template limitations
[3]	60 resumes	ML-based	Summarization, Entity extraction	~85% accuracy	No spatial modeling, weak generalization
[4]	Not specified	Mixed (Keyword + ML)	NLP, keyword matching	~70% accuracy	Poor contextual understanding
[5]	Literature-based	Rule-based (Survey)	Chronological parsing, analysis	N/A	No experimental validation
[6]	OCR-only docs	OCR	Text image recognition	~85% OCR accuracy	No classification or entity recognition
[7]	Business resumes	DL-based	OCR, Deep Learning pipeline	~90% accuracy	No spatial-semantic integration
[8]	English CVs	NLP + ML	NLTK-based entity recognition	Not specified	No section classification, shallow analysis
[9]	Polish IT resumes	Rule + ML	Section classification, heuristics	~88% F1-score	Not end-to-end, limited semantic modeling

As the table shows, while various parsing methods have been explored, most fail to simultaneously address spatial layout and deep semantic content. This motivates the currect hybrid OCR–XGBoost–Transformer pipeline, designed to provide accurate, adaptable, and context-aware resume information extraction.

This study investigates whether integrating spatial layout features with semantic models can improve the accuracy and adaptability of resume information extraction.

Specifically, we hypothesize that a two-stage pipeline—combining OCR-based spatial recognition, section classification using XGBoost, and contextual entity extraction via Transformers—will outperform traditional methods that rely solely on textual content.

To validate this hypothesis, our research follows four main objectives:

1. Analyze existing approaches and identify their limitations,
2. Construct and annotate a dataset of resumes with spatial and semantic labels,
3. Evaluate the performance of machine learning and deep learning models for section classification and entity recognition,
4. Design and implement an integrated, hybrid information extraction pipeline.

The main contribution of this work is the development of a novel solution that combines OCR for text recognition, ML algorithms for text line classification into appropriate sections, and semantic models based on Named Entity Recognition (NER) for information extraction. This integrated approach addresses both the visual-spatial aspects of resumes and their semantic content, providing more accurate and comprehensive information extraction than current systems.

The remainder of this paper is organized as follows: Section 2 describes the proposed methodology, including the system architecture, dataset preparation, feature

engineering, and algorithms employed. Section 3 presents the experimental results, including classification and entity recognition performance. Section 4 provides a discussion of the results in the context of existing work, with analysis of contributing factors and identified limitations. Finally, Section 5 concludes the paper by summarizing the contributions and outlining directions for future research.

2 Method

2.1 System architecture

The proposed system employs a multi-stage pipeline approach for automated information extraction from resumes. The overall architecture, illustrated in Figure 1, consists of three main components: (1) text recognition and extraction using OCR, (2) text classification to identify resume sections, and (3) semantic information extraction from the classified text segments.

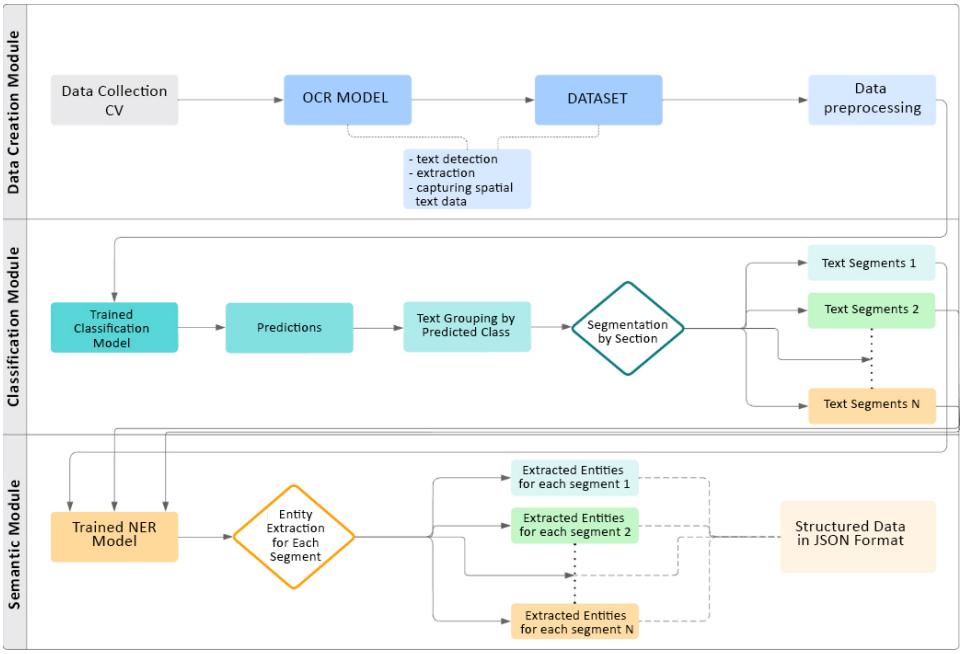


Figure 1: System architecture

The workflow begins with resume documents that are converted to images to ensure format independence. The PaddleOCR [10] model then processes these images to extract text and spatial coordinates. The extracted text lines are classified into appropriate resume sections using ML models. Finally, semantic models extract specific entities of interest from each classified section, such as candidate names, skills, education details, and work experience.

2.2 Dataset preparation and feature selection

2.2.1 Analysis of the Structure and Content of a CV

In preparing a CV, certain sections are commonly included to present relevant information for effective job applications. These sections typically include:

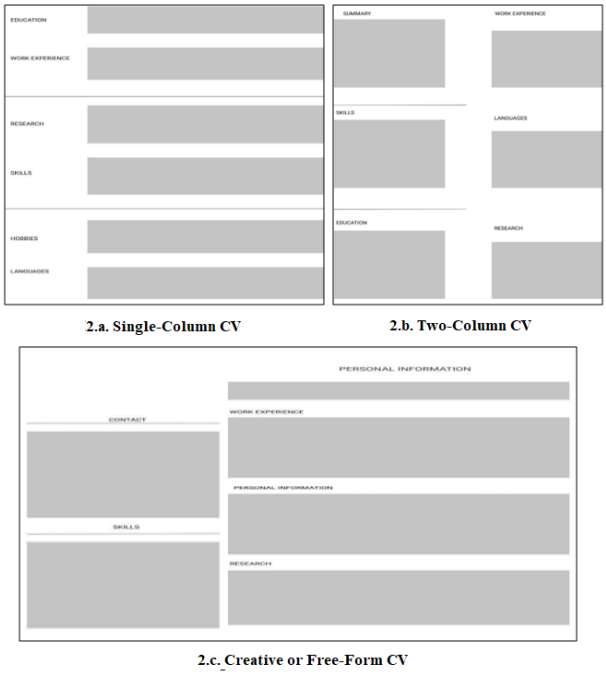
- **Personal Information:** Includes full name, address, phone numbers (home and mobile), email address, and optionally a personal website. This information allows employers to easily contact the candidate.
- **Career objective:** A short statement describing the candidate's professional goals and the type of position sought. This helps employers understand the candidate's motivations and expectations.
- **Education:** Lists academic background, including institutions attended, their locations, degrees obtained, and any relevant certifications or training.
- **Job-related skills:** Highlights specific skills relevant to the target job, whether acquired through work, internships, volunteer activities, or hobbies.
- **Professional experience:** Provides details on the candidate's work history, including company names, job titles, locations, dates of employment, and descriptions of roles and responsibilities. Relevant internships and volunteer experiences may also be included.
- **Additional information:** Covers elements that support the application such as language proficiency, computer skills, professional certifications, memberships in professional organizations, awards, and achievements. A portfolio may also be referenced if applicable.

- **Interests and activities:** Includes hobbies and leisure activities that reveal aspects of the candidate's personality and can highlight soft skills or additional qualifications.

There are four main types of CV formats, each designed to emphasize different aspects of a candidate's profile:

- **Chronological CV:** Lists the candidate's work history in reverse chronological order, starting with the most recent position. This is the most commonly used format and suits candidates with consistent career progression.
- **Functional CV:** Focuses on skills and competencies rather than the sequence of jobs. Ideal for candidates changing careers or with employment gaps, this format categorizes skills and highlights accomplishments over job history.
- **Targeted CV:** Tailored to a specific job by emphasizing the qualifications that best match the employer's expectations. It requires the candidate to carefully analyze the job posting and customize each CV section accordingly. **Combination CV:** Merges the chronological and functional formats. It begins with a summary of key competencies followed by a detailed chronological work history. This format suits candidates with both strong experience and specialized skills.

CVs can be presented in several visual formats. Figure 2 illustrates three common layout styles:



2.a. Single-Column CV 2.b. Two-Column CV

2.c. Creative or Free-Form CV

Figure 2: Common CV layout formats

- **Single-Column CV (Figure 2.a):** A traditional layout where sections are arranged vertically from top to bottom. It offers clarity and simplicity, making it easy for recruiters to read through the information.
- **Two-Column CV (Figure 2.b):** Divides the page into two main areas. The left column typically contains personal details and key skills, while the right includes professional experience, education, and other supporting content. This format improves information organization and visual balance.
- **Creative or Free-Form CV (Figure 2.c):** Often used in artistic or design-related fields, this format allows for greater customization, including asymmetric columns, infographics, colored blocks, or icons. It provides a personalized and visually distinctive presentation of qualifications.

Each of these formats offers unique advantages depending on the candidate's profile and the industry expectations.

2.2.2 Dataset construction for classification models

A dataset of 200 French resumes in PDF format was collected from the HR department of Intelcia IT Solutions [11]. Each resume was converted to image format to facilitate consistent processing across different layouts and styles. The PaddleOCR model was applied to extract both textual content and spatial information of each text line.

Feature engineering focused on capturing the spatial relationships between text lines and section headings within resumes. Two key types of features were developed:

1 Distance-based features: Normalized horizontal and vertical Euclidean distances between each text line and section headings were calculated. For text lines and section headings on different

pages, a specialized distance calculation was implemented that accounted for page breaks.

2 Positional features: Binary features indicating whether a text line appeared above or below each section heading were created and encoded using LabelEncoder.

3 The dataset was manually labeled with ten classes: nine representing common resume sections (Experience, Education, Skills, Projects, Certification, Languages, Interests, Software, and Personality) and a tenth class "Other" for text not belonging to any standard section. In total, 10,000 text lines were labeled to create the training corpus.

2.2.3 Dataset preparation for semantic models

For the semantic extraction task, text lines were grouped according to their predicted section classifications to provide contextual information. The Doccano annotation tool was used to manually annotate named entities within each section. A total of eight entity types were defined for annotation: Name, Email, Phone, Education, Experience, Skills, Language, and Certification. These categories were selected based on relevance to recruitment use cases and availability across most CVs in the dataset. The annotated text was then processed and converted to the JSONL format required by SpaCy [12] for NER model training.

2.3 Key algorithms

2.3.1 XGBoost for section classification

The eXtreme Gradient Boosting (XGBoost) algorithm was selected for resume section classification based on its superior performance. XGBoost is an ensemble learning method that builds sequential decision trees to minimize residual errors. It excels at capturing complex feature interactions and handling non-linear relationships [13].

The model was configured with the following hyperparameters:

- Maximum tree depth: 3
- Number of estimators: 100
- Learning rate: 0.1

This hyperparameter implementation allowed the model to balance complexity and generalization, as well as better capture the learning capabilities of the spatial features. XGBoost was also implemented very well in terms of its ability to mitigate model limitations from previous classification models we attempted in the study.

2.3.2 Artificial Neural Network for section classification

The Artificial Neural Network (ANN) was implemented as a multilayer perceptron with the following architecture:

- Input layer: Matching the dimensionality of the feature set
- Hidden layers: Two hidden layers with 64 and 32 neurons respectively
- Activation function: ReLU for hidden layers and Softmax for output layer
- Output layer: 10 neurons corresponding to the resume section classes

The model was configured with the following hyperparameters:

- Optimizer: Adam with learning rate of 0.001
- Loss function: Categorical cross-entropy
- Batch size: 32
- Training epochs: 50
- Early stopping: Patience of 5 epochs monitoring validation loss

ANNs were selected for comparison due to their proven effectiveness in text classification tasks and ability to learn complex non-linear relationships between features [14].

XGBoost was selected due to its proven performance in similar structured classification tasks. It offers efficient handling of sparse and imbalanced data, robust regularization, and interpretable feature contributions. As demonstrated later in Section 3, XGBoost outperformed alternatives such as Random Forest, ANN, and SVM, confirming its suitability for the classification of OCR-extracted resume sections.

2.3.3 Support Vector Machine for section classification

The Support Vector Machine (SVM) model was implemented with the following configuration:

- Kernel: Radial Basis Function (RBF)
- C parameter (regularization): 10
- Gamma parameter: 0.01
- Decision function: One-vs-Rest for multi-class classification
- Probability estimates: Enabled

SVMs were chosen for comparison due to their traditionally strong performance in text classification tasks with moderate-sized datasets and their effectiveness with high-dimensional feature spaces. The RBF kernel was selected after preliminary testing showed superior performance over linear and polynomial kernels for capturing the complex relationships in the spatial and positional features [15].

These implementations were evaluated using the same train-test split and evaluation metrics as the XGBoost model to ensure a fair comparison of performance across all three classification approaches.

2.3.4 Transformers model for named entity recognition

For the semantic information extraction component, a Transformers-based model was implemented using SpaCy's framework. The overall workflow for semantic model construction is illustrated in Figure 3.

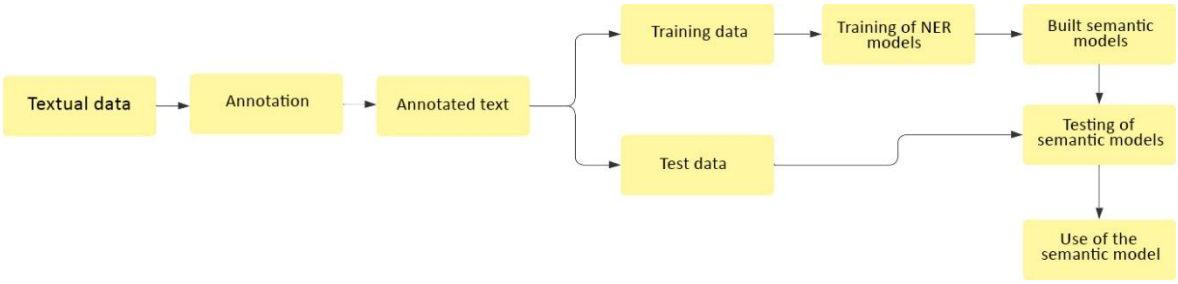


Figure 3: General workflow for semantic model construction

Transformers use an attention mechanism to capture contextual relationships between words in text sequences [16]. The semantic extraction model was built using the CamemBERT-based Transformer model, implemented through SpaCy v3.5 using the fr_dep_news_trf pipeline. CamemBERT is pretrained on large-scale French-language datasets (including OSCAR and CCNet) and employs a SentencePiece tokenizer. This choice ensured linguistic compatibility with the French resume dataset used for training. The model was fine-tuned on eight entity categories (Name, Email, Phone, Education, Experience, Skills, Language, and Certification) for 80 epochs, using the Adam optimizer and a warm-up learning rate schedule with early stopping enabled.

Training was conducted on a standard GPU environment available using Google Colab, with an average epoch runtime of 4 minutes and a total training duration of approximately 5.5 hours. The final model was exported in SpaCy's DocBin format for deployment.

The workflow begins with the classified text segments from the previous stage, which are then processed for annotation. After manual annotation using Doccano, the annotated text data is preprocessed and structured into the required format for model training. The model is then trained using the prepared dataset and evaluated against test data before final deployment.

The model was configured using a base configuration file that defined:

- Architecture parameters
- Training hyperparameters
- Optimizer settings
- Feature extraction components

The Transformers model was selected because of its ability to capture long-distance dependencies and contextual information, which is particularly valuable for identifying named entities in resume text where formatting and context provide important cues.

2.4 Evaluation metrics

Performance evaluation for both classification and NER models was conducted using standard metrics for multi-class classification problems [17]. First, the basic metrics for a single class are defined in equations 1 to 4:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{P} = \frac{TP}{TP + FN} \quad (3)$$

$$F1\ Score = \frac{2 \times Recall\ \times\ Precision}{Recall + Precision} \quad (4)$$

Where:

- TP: True Positive, the number of cases where the model correctly predicts a positive class
- TN : True Negative, the number of cases where the model correctly predicts a negative class
- FP : False Positive, the number of cases where the model incorrectly predicts a positive class
- FN : False Negative, the number of cases where the model incorrectly predicts a negative class

Then, for the multi-class evaluation in this study, macro-averaging was employed, which calculates in the equations 5 and 6 the metric independently for each class and then takes the average. This approach gives equal weight to all classes regardless of their frequency in the dataset:

$$Precision_{macro\_average} = \frac{1}{n}\sum_{k=1}^{n} P_k \quad (5)$$

$$Recall_{macro\_average} = \frac{1}{n}\sum_{k=1}^{n} R_k \quad (6)$$

Where P_k is the precision for class k, $R_k$is the recall for class k, and n the total number of classes. This evaluation ensures that performance on less frequent resume sections was properly assessed [18].

2.5 Pipeline overview – pseudocode

The full hybrid workflow is summarized below to illustrate the integration of the components described above.

Algorithm 1. Hybrid Resume Parsing Pipeline

Input: resume_dataset – a collection of resumes in PDF format

Output: Structured data with section labels and extracted named entities

```
for each resume in resume_dataset do
    image ← convert_to_image(resume)
    ocr_output ← apply_PaddleOCR(image)
    lines_with_coords← extract_text_lines_with_positions(ocr_output)
    classified_sections ← XGBoost_classify(lines_with_coords)
    for each section in classified_sections do
        ner_entities ← CamemBERT_NER(section.text)
        store(section.label, ner_entities)
    end for
end for
```

3 Experimental results

3.1 Performance comparison of classification models

The evaluation of the three classification models (ANN, SVM, and XGBoost) was conducted using a test dataset comprising 20% of the labeled data. Table 2 and figure 3 present a comparative analysis of their performance based on the evaluation metrics.

Table 2: Performance comparison of ANN, SVM, and XGBoost Algorithms

Model	Accuracy	Macro-average precision	Macro-average recall	Macro-average F1-Score
ANN	80.7%	65.7%	77.2%	71.0%
SVM	72.5%	51.8%	66.7%	58.3%
XGBoost	96.5%	94.7%	95.3%	95.0%

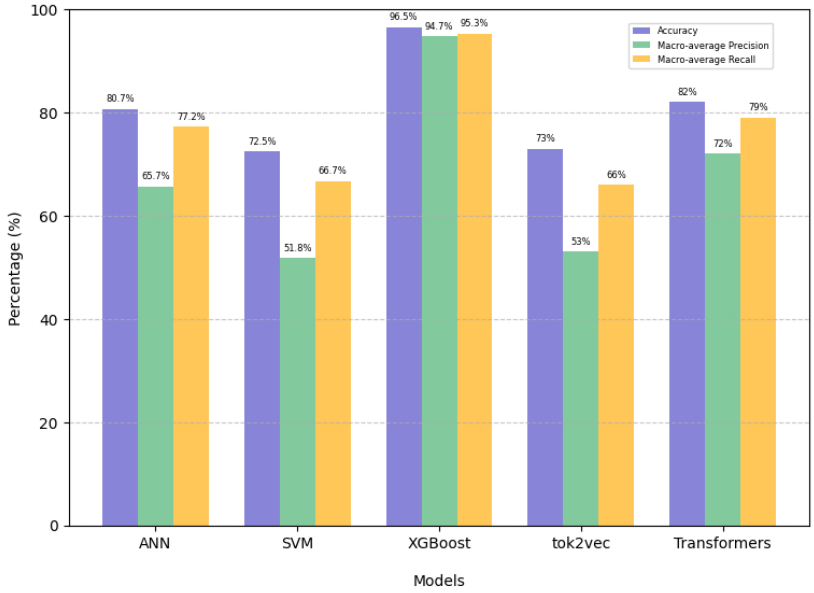


Figure 4: Performance comparison of classification and NER Models

As evident from Table 2 and figure 4, XGBoost significantly outperformed the other models across all metrics. The model achieved an impressive accuracy of 96.5%, indicating its superior ability to correctly classify text lines into their respective CV sections. Furthermore, the high macro-average precision (94.7%) and recall (95.3%) values show XGBoost's robust performance across all classes, including minority classes.

3.2 Performance of semantic models for named entity recognition

Two NER models were evaluated for their effectiveness in extracting named entities from the classified text: tok2vec and Transformers. Table 3 summarizes their performance after 80 training epochs.

Table 3: Comparison of NER Models: tok2vec and Transformers

Model	Accuracy	Macro-average precision	Macro-average recall	Macro-average F1-Score
tok2vec	73%	53%	66%	58.7%
Transformers	82%	72%	79%	75.3%

The Transformers model beat the tok2vec on the evaluation metrics overall. With an accuracy of 82%, the Transformers model was more accurate when classifying named entities in resume text.

3.3 Analysis of XGBoost's superior performance

XGBoost's better performance can be attributed to several factors related the nature of the algorithm:

- **Boosting technique:** XGBoost is based on a gradient boosting method that sequentially builds

new models to correct the mistakes of prior models. XGBoost is able to learn from previously misclassified items and iteratively improves prediction performance.

- **Handling complex data:** XGBoost can fit complex relationships between features, and moreover, can capture non-linear relationships. This is significant for resume texts where the spatial relationship between the text lines and section headings influences their classification.
- **Feature importance analysis:** The algorithm, in its own fashion, defines the most useful features, and classifier performance improves by emphasizing the most important features.
- **Regularization techniques**: It is noteworthy to say that XGBoost uses regularisation parameters that can assist with the likelihood of overfitting, adding to the good performance of the model on unseen data.

Figure 5 shows the confusion matrix for the XGBoost model which is indicative of its overall, high classification performance across all CV sections.

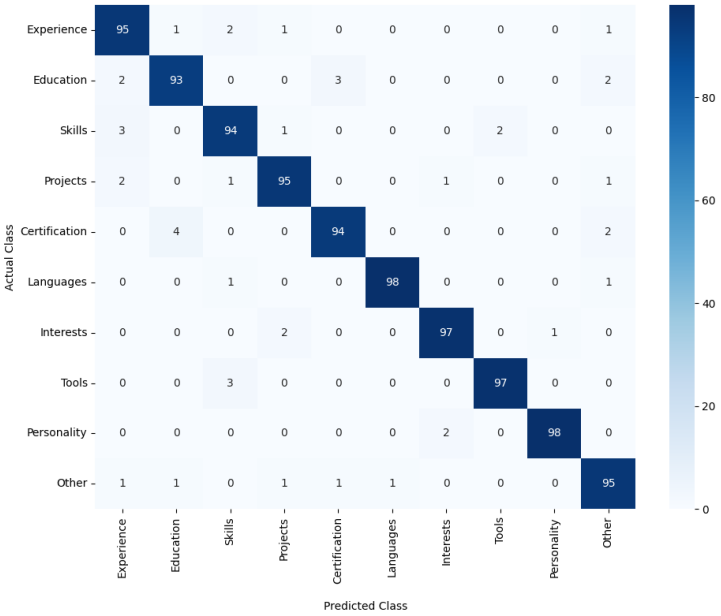


Figure 5: Confusion matrix for XGBoost Model (values in %)

The matrix shows a very high level of accuracy (93-98%) with virtually no confusion across sections where error estimates like Experience and Projects only had a 1-2% estimating error, showcasing how well the XGBoost method was able to handle the complexity of resume data.

3.4 Transformers model performance analysis

The superior performance of the Transformers models generally in NER task has many reasons:

- **Attention mechanism:** The Transformers model uses an attention mechanism that enables it to model contextual relationship between words. It can inspect words within a larger context where it is appearing, which enhances the accuracy of entity recognition.
- **Contextual understanding:** Rather than only focusing on the local patterns in the word sequences like in the tok2vec model, the Transformers model can also model the long-distance dependency between the words to get a more comprehensive understanding of all context in the text.
- **Sequential processing advantage:** The classification of individual lines of text accurately positioned the model to better achieve entity extraction in the Transformers module with better understanding of context.

3.5 Significance of the two-stage approach

An important finding of this research is the utility of the two-stage information extraction process:

1. The first stage incorporates XGBoost to classify each of the text lines into its respective CV section to help clarify for semantic analysis.
2. The second stage incorporates the Transformers model, which analyses the semantic meaning and extracts the relevant entities.

This process provides a solution to one of the main challenges of resume parsing, which was the distribution of the spatially located text within the image. By incorporating the organization of the text into sections before doing a semantic analysis, we are able to achieve a higher degree of accuracy with information extraction than purely undertaking a semantic analysis of the CV.

The results also indicate that the semantics of translating visually oriented information into semantic information creates an additional language processing dimension that

goes beyond a one-dimensional text analysis and includes both visual information and spatial language processing.

4 Discussion

The results presented in the previous section demonstrate that the hybrid pipeline outperforms traditional resume parsing approaches in terms of accuracy, generalization, and contextual understanding. Specifically, the XGBoost classifier achieved a 96.5% accuracy in section classification, and the Transformers model reached 82% accuracy in named entity recognition.

When compared to prior studies summarized in Table 1:

- Methods relying on rule-based or keyword techniques [1], [2], [4] showed limited adaptability to diverse resume formats and lacked semantic depth.
- Machine Learning-only approaches such as [3] achieved moderate performance (~85%) but did not incorporate spatial features or layout context.
- Deep Learning models in [7], although promising (~90%), still treated resumes as flat text, without segment-level classification or layout awareness.

In contrast, the proposed pipeline integrates both spatial (layout-aware) features and semantic (contextual) representations, which contributes to improved classification and entity recognition. The two-stage design ensures that the semantic model receives pre-structured input, enhancing its ability to extract relevant entities with higher precision.

The superior performance of the XGBoost model can be attributed to:

- Fine-grained spatial features (e.g., distances, relative positions),
- Strong regularization and ensemble learning characteristics,
- Efficient handling of imbalanced or non-linear class boundaries.

Likewise, the use of Transformers for NER offers advantages in:

- Capturing long-range dependencies across lines within the same section,
- Handling resume-specific terminology through contextual embeddings,
- Generalizing well across structurally diverse documents.

Some failure cases were observed in:

- Highly unstructured or creative resume formats (e.g., asymmetric layouts),
- Multilingual resumes, where OCR and entity recognition performance dropped,
- Misclassification between "Projects" and "Experience" when boundaries were unclear.

These cases highlight potential improvements through layout-aware Transformers or multimodal embeddings that fuse visual and textual signals.

5 Conclusion

This research introduces a novel hybrid AI solution for automated resume information extraction, combining OCR with Machine Learning for text classification (achieving 96.5% accuracy with XGBoost) and Deep Learning for semantic understanding (reaching 82% accuracy with Transformers). The approach addresses the challenge of resumes as spatially distributed text, where both layout and content provide crucial semantic context, demonstrating that considering spatial positioning enhances resume parsing accuracy.

While the current implementation faces limitations including language dependency, sensitivity to extreme formatting variations, and substantial training data requirements, several promising research directions emerge. Future work should explore deeper integration of visual and semantic elements, extend the approach to multi-dimensional text analysis beyond traditional linear processing, and investigate techniques requiring less labeled training data. This research ultimately points toward a new domain of natural language processing that incorporates spatially-oriented language understanding with applications extending beyond resume parsing to other complex document types.

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Deformation Suppression Method for the CNC Machining Process of Parts Based on a Single Neuron PID

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Keywords: CNC machining, deformation suppression, single-neuron PID, predictive control, smart manufacturing

Received: May 16, 2025

Computer Numerical Control (CNC) machining plays a vital role in modern precision manufacturing but often suffers from part deformation due to thermal and mechanical stresses, compromising dimensional accuracy. Traditional CNC systems lack adaptive intelligence, operating with static parameters and failing to address real-time deformation risks. This study proposes an intelligent deformation suppression method using a lightweight single-neuron-based Proportional-Integral-Derivative (PID) neural model, termed NeuroPID-CNC, to predict and mitigate deformation during machining. The model was trained and tested on the CNC-DeformControl dataset containing machining parameters such as cutting speed, feed rate, depth of cut, tool temperature, and material type. Data preprocessing involved normalization and categorical encoding. The NeuroPID-CNC model, structured as a binary classifier with a single hidden neuron using a sigmoid activation function and Adam optimizer, was trained on 70% of the data and evaluated on the remaining 30%. It achieved 92% accuracy, 90% precision, 93% recall, 91.5% F1-score, and 0.84 MCC, outperforming conventional algorithms like SVM, RF, LR, and KNN. A real-time feedback loop further enables adaptive learning. The NeuroPID-CNC approach effectively predicts deformation risks and recommends real-time control actions, enhancing machining reliability and reducing material waste. This makes it a promising solution for smart, adaptive manufacturing environments.

Povzetek: Za preprečevanje deformacij med CNC obdelavo je predlagana metoda NeuroPID-CNC, lahki nevronski model z enim nevronom, ki posnema PID regulator. Model je dosegel visoko točnost pri napovedovanju tveganja deformacije in priporoča prilagoditve v realnem času (npr. hitrost rezanja), s čimer izboljša zanesljivost in kakovost izdelkov.

1 Introduction

1.1 The background information of this scientific field

Computer Numerical Control (CNC) machining is an essential component of modern industrial manufacturing, allowing for the automated, precise fabrication of complex components from a broad range of materials, including metals, plastics, and composites [1]. CNC machines use programmed instructions to control parameters like cutting speed, feed rate, tool path, and spindle load [2]. This high level of automation improves productivity, consistency, and precision in industries ranging from aerospace, automotive, and electronics. However, as manufacturing tolerances tighten and precision requirements rise, even minor distortions during machining can result in unacceptable defects, raised rework rates, and wasted resources. These distortions, often referred to as machining-induced deformations, are impacted by numerous factors such as tool temperature, material type, cutting forces, and vibration during the machining process.

1.2 The current knowledge and advances in this field

Sensor integration, adaptive control systems, and advanced simulation techniques have all contributed significantly to the advancement of CNC machining in recent years [3]. Researchers and engineers have used finite element modeling (FEM), real-time feedback systems, and machine learning techniques to track and improve machining processes [4]. Numerous studies have concentrated on predicting tool wear, improving cutting conditions, and enhancing the surface finish [5]. Adaptive control algorithms like fuzzy logic, conventional PID controllers, and deep learning-based methods have been proposed to tackle machining variability. Despite these improvements, numerous control systems still depend on

fixed or heuristic-based logic that cannot continuously learn or adapt to the machining setting.

1.3 The current problem/issue that needs to be solved or addressed urgently

One of the most persistent and pressing issues in CNC machining is the inability of current systems to forecast and avoid part deformation in real time [6]. Deformation causes dimensional inaccuracies, structural weaknesses, and higher manufacturing costs [7]. Existing PID controllers and other conventional control strategies are not well-suited to capture the nonlinear, dynamic nature of machining-induced deformation, particularly in high-speed or multi-material machining settings [8]. Additionally, there is a lack of lightweight and interpretable models that can operate in real-time, continuously adapt to novel machining data, and offer actionable parameter adjustments to minimize deformation risks [9], [10]. The followings are the hypotheses:

- Whether a single-neuron-inspired PID control model accurately forecast the risk of component deformation in CNC machining by utilizing real-time machining parameters?
- Does the application of a single-neuron-inspired PID control algorithm lead to a substantial decrease in part deformation when compared to conventional static or PID-based control methods?
- Can the dynamic modification of cutting conditions, informed by the predictions of the single-neuron PID model, enhance component quality and machining reliability?
- Whether a single-neuron neural model more effectively forecast deformation risks in real-time CNC operations compared to conventional classifiers?

1.4 The purpose(s) of doing this research

The primary goal of this research is to create an intelligent deformation suppression control algorithm specifically designed for CNC machining environments. The study aims to design and execute a single-neuron-inspired PID model that can precisely forecast the risk of part deformation using real-time machining parameters. This study also aims to offer practical control suggestions for dynamically adjusting cutting conditions to prevent deformation, resulting in improved part quality and machining dependability. The study addresses the gap in lightweight, adaptive, and responsive control systems appropriate for contemporary smart manufacturing setups.

1.5 The main method(s) used in this research

To achieve the research objectives, a novel algorithm called NeuroPID-CNC was created and trained on a curated dataset called CNC-DeformControl, which includes critical machining parameters like cutting speed, feed rate, depth of cut, tool temperature, material type, and others. The methodology included several key stages: data preprocessing by categorical encoding and normalization; building of a lightweight single-neuron neural network model that simulates PID control behavior; training and evaluation of the model utilizing binary classification metrics such as accuracy, precision, recall, and F1-score; and integration of a real-time feedback strategy to allow online learning and continual enhancement. To guarantee efficient convergence and computational effectiveness, the model makes use of a sigmoid activation function, binary cross-entropy loss, and the Adam optimizer. In addition, real-time control logic is integrated into the system, allowing it to automatically adjust crucial machining parameters, such as coolant flow, cutting speed, and feed rate, when a high deformation risk is predicted.

1.6 The importance or impact of this research to the scientific community

This study contributes to the improvement of intelligent CNC control systems by proposing an interpretable and adaptive control framework that combines conventional PID principles and neural learning capacities. By incorporating a single-neuron PID architecture, the algorithm guarantees low computational overhead while providing intelligent decision-making in real time. The NeuroPID-CNC method can be incorporated into industrial CNC machines to significantly decrease material waste, enhance product quality, and lower operating costs. For the scientific community, this research opens up new avenues for creating hybrid neuro-control systems, expanding the scope of Industry 4.0, and supporting the evolution of automated manufacturing methods.

Controlling deformation and guaranteeing dimensional accuracy of machined parts has proven to be a significant difficulty in CNC machining due to the dynamic and complex nature of the process. Fan et al. [11] proposed an energy-based principle for reducing machining distortion in monolithic aircraft parts, which provided insights into residual stress release and deformation prediction. However, their method lacked a real-time compensation mechanism. Ma et al. [12] proposed a single-neuron PID-based model that showed success in deformation suppression during CNC machining, but it was tested under limited scenarios and did not take parameter adaptability into account in real time. Kasprowiak et al. [13] used input shaping control to decrease machining vibration, but they neglected to consider feedback

adaptation during continuous machining. Similarly, Guo et al. [14] concentrated on suppressing casing vibrations in aeroengine elements but did not integrate with tool-path compensation.

Shi et al. [15] presented a compensation model for polishing tools in precision CNC polishing, which enhanced surface quality but was only applicable to aspheric surfaces. Hasçelik et al. [16] optimized cutting parameters to reduce wall deformation in thin-wall micro-milling. However, their approach was sensitive to tool wear and material variability. Zheng et al. [17] investigated vibration-assisted micro-milling, which provided useful insight into tool wear reduction but lacked general applicability. Gan et al. [18] presented an adaptive backlash compensation method for CNC machines, but its effectiveness in complex geometries remains unverified.

Świć et al. [19] studied control methods for elastic-deformable states in turning and grinding shafts. However, their focus was on low-stiffness shafts, which limits generalization. Lv et al. [20] created an automated shape correction mechanism for wood composites, emphasizing possibilities in non-metallic materials but having limited application to high-precision metal machining. Yi et al. [21] investigated mesoscale deformation in thin-walled micro-milling, but did not use intelligent adaptive feedback systems. Korpysa and Habrat [22] explored precision milling of magnesium alloys, comparing coated and uncoated tools, but lacking dynamic deformation control. Devi et al. [23] used ant lion optimization with TOPSIS analysis to optimize milling parameters, but their method did not include predictive modeling or feedback control. Table 1 shows a summary of related works.

Table 1: Summary of related works

Ref	Study Focus	Results	Limitations
[11]	Energy principle for distortion reduction in aircraft parts	Enhanced prediction of residual stress-related deformation	No real-time compensation mechanism
[12]	Single-neuron PID model for deformation suppression	Efficient in simple deformation control	Not tested under varied real-time conditions
[13]	Input shaping control for vibration suppression	Decreased vibration efficiently	Lacked adaptive feedback integration
[14]	Vibration suppression in aeroengine casing milling	Improved structural stability	Did not incorporate tool-path compensation
[15]	Tool displacement model for CNC polishing	Enhanced surface finish in aspheric polishing	Particular to aspheric surfaces only
[16]	Optimization in micro-milling of thin-wall geometries	Decreased deformation utilizing optimized parameters	Sensitive to tool wear and material variability
[17]	Tool wear suppression in vibration-assisted micro-milling	Reduced wear through non-resonant vibration	Limited generalization across materials
[18]	Adaptive backlash compensation in CNC	Decreased mechanical play in motion systems	Unproven effectiveness for complex parts
[19]	Elastic-deformable state control in shaft machining	Enhanced dimensional accuracy in low-stiffness components	Applicable mostly to the turning and grinding of shafts
[20]	Shape correction in wood composites	Automated geometric adjustment during continuous pressing	Limited relevance to metal CNC applications
[21]	Deformation control in mesoscale micro-milling	Superior precision in curved thin-wall parts	No intelligent feedback or real-time control
[22]	Milling accuracy in magnesium alloys	Enhanced accuracy utilizing coated tools	No active deformation control included
[23]	End-milling parameter optimization using ant lion and TOPSIS	Multi-objective optimization attained	Static optimization lacks predictive adaptability

The prior investigations combined offer valuable insights into machining vibrations, deformation mitigation, parameter optimization, and compensation methodologies. Nonetheless, several restrictions and substantial gaps persist in the integration of real-time intelligent control, including the absence of adaptive feedback, active deformation control, and model interpretability, among others. This research proposes a lightweight and effective framework, termed the NeuroPID-CNC model, to address the limitations and research gaps identified in prior studies.

2 Materials And methods

This section describes the creation of the NeuroPID-CNC Algorithm, which predicts and suppresses deformation in CNC machining. The NeuroPID-CNC algorithm is a smart deformation suppression control algorithm designed to predict and reduce the risk of part deformation during CNC (Computer Numerical Control) machining processes. It draws on both machine learning and PID control principles, combining the intelligence of a lightweight neural network with real-time process control strategies. NeuroPID-CNC employs a single-neuron neural network that mimics a PID controller. It accepts machining parameters as input (for example, cutting speed, feed rate, depth of cut, and temperature) and predicts whether deformation will occur ("Yes" or "No"). If there is a high risk of deformation, the algorithm automatically adjusts the machining settings to prevent it. Algorithm 1 shows theNeuroPID-CNC algorithm.

Algorithm 1: NeuroPID-CNC

Input: CNC-DeformControl Dataset (features + Deformation Risk)
Output: Predicted Deformation Risk (Yes/No) and control recommendations

Begin
// **Step 1: Data Preprocessing**
Load dataset D
Encode categorical attributes in D
Normalize numerical attributesin D
Split D into training_set and test_set (70/30)

// **Step 2: Initialize Single-Neuron PID Model**
Initialize neural network:
- 1 input layer
- 1 hidden layer with 1 neuron (PID-like)
- 1 output neuron (binary classification)

Set activation_function ← Sigmoid
Set optimizer ← Adam
Set loss_function ← Binary Crossentropy
Set biases to zero
Employ Glorot Uniform for weight initialization.
Implement L2 regularization and configure the batch size to 32.
Establish the epoch count at 100.
// **Step 3: Training Phase**
Train the model on the trainingset utilizing backpropagation
For each period (1 to 100):
Randomize training dataset
Segment the data into mini-batches of size 32.
For each mini-batch:
Calculate the output of the hidden layer utilizing the sigmoid function.
Calculate the output layer utilizing the sigmoid function.
Calculate the binary cross-entropy loss between the expected and actual outputs.
Calculate loss
Adjust weights and biases via the Adam optimizer
Implement L2 regularization during weight adjustments.
Apply early stopping to prevent overfitting

// **Step 4: Evaluation Phase**
Assess the model on the test set
Calculate Accuracy, Precision, Recall, F1-Score, and MCC
Display the confusion matrix

// **Step 5: Real-Time Prediction & Control**
For each newinput:
Encode and normalize new_input
prediction ← model.predict(new_input)

```
    If prediction == "Yes" then
      Decrease Cutting Speed
       Increase Coolant Flow
       Adjust Feed Rate based on Material Type
    Else
       Continue with current parameters
    End If

// Step 6: Feedback Loop
After machining:
    Record actual deformation findings
    Compare the prediction with the actual outcome
    Update model weights via online learning

End
```

The NeuroPID-CNC algorithm is a smart deformation suppression control system specifically designed for CNC machining applications. It employs a lightweight neural network model that simulates PID behavior using a single-neuron architecture to predict whether a machined part is deformable based on a variety of machining parameters such as cutting speed, feed rate, depth of cut, tool temperature, material type, and others. The process begins with preprocessing the CNC-DeformControl dataset by encoding categorical features and normalizing numerical ones, then splitting the data into training and testing sets. The neural model, which includes a sigmoid-activated hidden neuron, is trained with the Adam optimizer and binary cross-entropy loss. After training, it uses standard classification metrics to evaluate previously unseen data and predicts deformation risk for new machining conditions in real time. If a high deformation risk is detected, the algorithm adjusts machining parameters dynamically, such as reducing cutting speed, increasing coolant flow, or changing the feed rate based on material properties, to reduce deformation. A feedback mechanism is integrated to continuously update the model through online learning, improving control accuracy over time. Figure 1 shows the flow diagram of the NeuroPID-CNC algorithm.

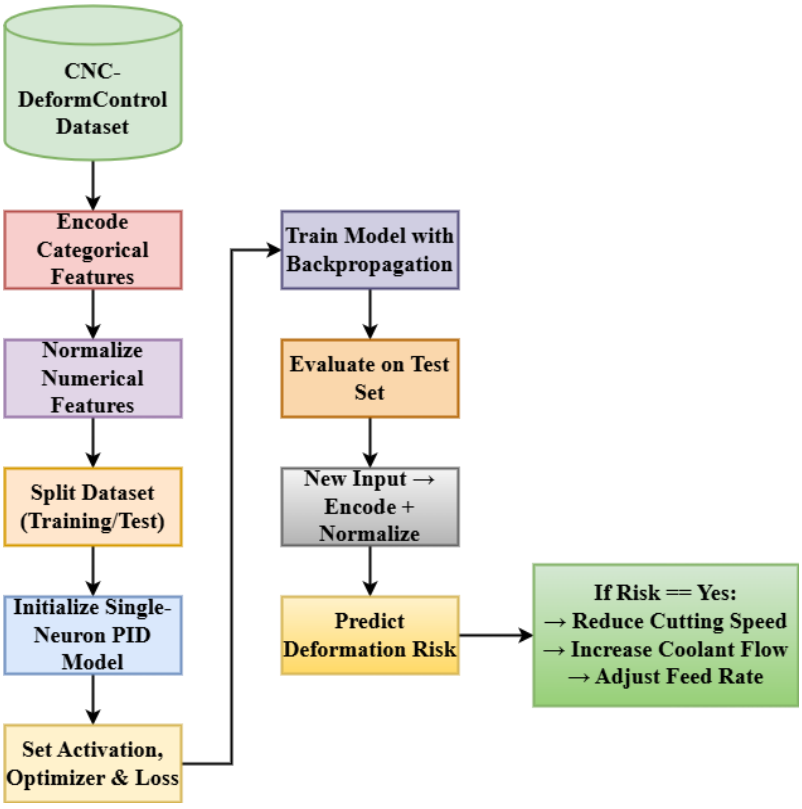

Figure 1: Flow diagram of NeuroPID-CNC algorithm

The flow diagram shows the NeuroPID-CNC algorithm's operational pipeline for predicting and controlling deformation during CNC machining. It starts with the CNC-DeformControl dataset, which goes through preprocessing steps such as categorical feature encoding and numerical feature normalization to ensure algorithm compatibility. The data is then divided into training and testing sets to aid in model generalization. A single-neuron PID-inspired neural network is set up with a sigmoid activation function, Adam optimizer, and binary cross-entropy loss function. The model is trained with backpropagation and evaluated on the test set to compute performance metrics. For real-time predictions, incoming data is encoded and normalized similarly, and the model predicts the deformation risk. If the risk is identified as "Yes," corrective control actions are automatically triggered, including reducing cutting speed, increasing coolant flow, and adjusting the feed rate based on the material type, allowing adaptive, intelligent CNC machining.

2.1 Dataset description

The CNC-DeformControl dataset is a curated collection of machining data designed to help intelligently predict and suppress part deformation during Computer Numerical Control (CNC) operations. It includes 11 key attributes, such as machining process parameters and observed outcomes, spread across several representative entries. The dataset's primary goal is to help machine learning applications, particularly the NeuroPID-CNC algorithm, understand how different machining conditions affect the likelihood of part deformation.

This dataset contains a mixture of numerical and categorical features. The numerical attributes—Cutting Speed (in RPM), Feed Rate (in mm/rev), Depth of Cut (in mm), Tool Temperature (in °C), and Spindle Load (as a percentage)—measure the operational intensity of machining. These parameters have a direct impact on heat generation, mechanical stress, and material removal efficiency. In contrast, categorical attributes such as material type (e.g., aluminum, steel, brass, plastic), tool wear, vibration, coolant flow, and surface finish provide qualitative information about the machining environment. These factors have an impact on part integrity through physical wear, thermal control, and vibration dampening. The Deformation Risk field, labeled as "Yes" or "No," serves as the target variable that indicates whether the machined part showed signs of deformation under the given conditions.

The data was gathered in a controlled CNC machining lab environment outfitted with industrial-grade sensors and monitoring equipment. Cutting speed, feed rate, and depth of cut were programmed and recorded directly from the CNC machine interface. Thermal readings were obtained using infrared sensors mounted near the tool-workpiece interface, and spindle load values were derived from the spindle drive system's onboard diagnostics. Categorical variables, such as tool wear and vibration levels, were evaluated using image-based inspection, vibration sensors, and operator feedback. Surface finish was determined by post-process optical inspection and tactile comparison with standard roughness gauges.

All collected data was logged in real time by a dedicated data acquisition system and then stored in a structured format in a relational SQL database hosted on a secure local server. Data from this database was exported in CSV format for preprocessing and training. The dataset is kept in a version-controlled environment to ensure data integrity and traceability during the algorithm development and testing stages. Figure 2 illustrates the data collection process in a controlled CNC machining lab environment.

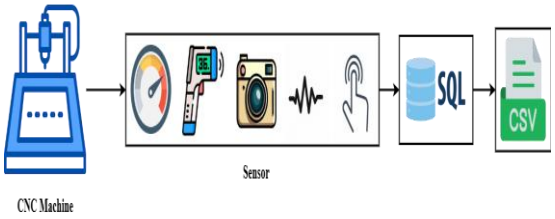

Figure 2: Data collection process

The CNC machine performs operations while sensors and tools collect relevant data. Machine diagnostics (speedometer icon) record cutting speed and feed rate, infrared sensors measure thermal data (thermometer icon), image-based analysis inspects tool wear (camera icon), vibrations are monitored by dedicated sensors (waveform icon), and surface finish is assessed by tactile comparison to roughness gauges (touch icon). All sensor data is captured in real time and securely stored in a structured SQL database (database icon). For model training and analysis, data is exported from SQL and converted to CSV format (CSV file icon). This pipeline provides high-quality, structured data for machine learning applications in deformation risk prediction.

Overall, the CNC-DeformControl dataset provides a compact but meaningful representation of the machining landscape, capturing both measurable and observational variables required for training intelligent deformation prediction systems like NeuroPID-CNC.

2.2 Data preprocessing

To ensure that the CNC-DeformControl dataset is ready for machine learning, extensive preprocessing steps are used. The dataset contains a mix of numerical and categorical features that must be represented consistently for the algorithm to correctly interpret the data. Categorical attributes like Material Type, Tool Wear, Vibration, Coolant Flow, and Surface Finish are

numerically encoded using one-hot encoding, which converts categorical values into a binary matrix format. The one-hot encoding process transforms a categorical variable into a binary vector representation as shown in Eq. (1):

$$OneHot(x_i) = [x_i = c_1, x_i = c_2, \dots, x_i = c_n] \quad (1)$$

Where:
x_i is a categorical value,
$c_1, c_2, \dots, c_n$ are the unique categories,
Each comparison $x_i = c_j$yields 1 if true, else 0.
This transformation is critical for allowing the single-neuron model to interpret non-numeric data while preserving categorical relationships without imposing artificial ordering.
Simultaneously, all numerical attributes—Cutting Speed, Feed Rate, Depth of Cut, Tool Temperature, and Spindle Load—are normalized utilizing Min-Max scaling, which rescales each feature to lie within the range [0, 1]. This is mathematically expressed by Eq. (2):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Where:
x = original value of the feature
x_{min}= minimum value of the feature in the dataset
x_{max}= maximum value of the feature in the dataset
x_{norm}= normalized value of the feature
This normalization ensures that no feature dominates others due to varying scales, resulting in balanced contributions throughout training. After normalization and encoding, the dataset is randomly divided into two subsets: 70% for training and 30% for testing. This split preserves model generalization and ensures that evaluation is performed on unseen data. The dataset D is randomly split into training and testing subsets using the Eq. (3):

$$D = D_{train} \cup D_{test}, \quad where\ |D_{train}| = 0.7|D|, \ |D_{test}| = 0.3|D| \quad (3)$$

Where:
D: The complete preprocessed dataset after normalization and encoding.
D_{train}: The training subset of the dataset utilized to train the model.
D_{test}: The testing subset of the dataset utilized to evaluate the model's performance.
|D|: The total number of data instances (rows) in the full dataset D.
$|D_{train}|$: The number of instances in the training set, equal to 70% of the total dataset.
$|D_{test}|$: The number of instances in the test set, equal to 30% of the total dataset.

2.3 Model initialization: Single-Neuron PID structure

The proposed model is a simple neural structure inspired by the PID control principle that consists of only one hidden neuron. This neuron simulates the adaptive control behavior of a PID controller by receiving preprocessed machining inputs from the input layer and computing a nonlinear transformation for prediction. The final output is produced by a single output neuron equipped with a sigmoid activation function, which converts the weighted sum of inputs into a deformation probability expressed by Eq. (4):

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (4)$$

Where:
z = weighted sum of inputs
σ(z) = output value in the range [0, 1] representing deformation risk
The term e^{-z}represents the exponential function with a negative exponent, which is a fundamental mathematical expression describing exponential decay. It is the inverse of the natural exponential function e^{z}, where e is Euler's number (approximately 2.71828). This function plays a key role in the sigmoid activation function by controlling how sharply the output transitions between 0 and 1 based on the input z.
Mathematically, e^{-z}can be expressed using its infinite series expansion in Eq. (5):

$$e^{-z} = \sum_{n=0}^{\infty} \frac{(-z)^n}{n!} \quad (5)$$

where:
z is the weighted sum of inputs,
$n!$ denotes the factorial of n,
and the series sums over all non-negative integers n.
This logistic function guarantees that the model's output lies between 0 and 1, representing the probability of deformation risk under current machining conditions. The model is trained utilizing the binary cross-entropy loss function, defined in Eq. (6), which measures the discrepancy between predicted and actual outcomes:

$$L = -[y.\log(\hat{y}) + (1 - y).\log(1 - \hat{y})] \quad (6)$$

Where:
y = actual class label (0 for no deformation, 1 for deformation)
$\hat{y}$= predicted probability of deformation
L = loss value that penalizes prediction errors
Here, y is the actual binary label (0 for "No Deformation" and 1 for "Yes"), while $\hat{y}$ is the predicted probability. The model's weights are optimized utilizing the Adam

optimizer, a robust gradient descent variant that adapts learning rates for quicker and more stable convergence. At each iteration t, the parameters $\theta_t$are updated as follows:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \quad (7)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) {g_t}^2 \quad (8)$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \quad (9)$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (10)$$

$$\theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (11)$$

where $g_t$is the gradient at iteration t, $m_t$and $v_t$are the biased first and second moment estimates, $\hat{m}_t$and $\hat{v}_t$are their bias-corrected estimates, α is the learning rate, $\beta_1$and $\beta_2$are decay rates for these moments, and ϵ is a small constant to prevent division by zero.

2.4 Training phase

During training, the model aims to reduce the loss function via backpropagation, an algorithm that calculates the gradient of the loss concerning each model weight. The weight update rule is formalized as showed in Eq. (12):

$$\Delta w = -n.\frac{\partial L}{\partial w} \quad (12)$$

Where:
w = change in weight
η = learning rate
$\frac{\partial L}{\partial w}$= gradient of the loss function concerning weight w

The training process iterates through numerous epochs, adjusting weights after each batch of training examples. To prevent overfitting, early stopping is executed: training halts if the validation loss fails to improve over a predefined number of epochs. This strategy improves model generalization on new, unseen CNC conditions.

2.5 Evaluation phase

After training, the model's efficiency is assessed on the testing set utilizing standard classification metrics. These metrics assess the model's capability to correctly predict deformation risk:
Accuracy measures the ratio of correct predictions to total samples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

Where,
TP = True Positives (correctly predicted deformations)
TN = True Negatives (correctly predicted non-deformations)
FP = False Positives (incorrectly predicted deformations)
FN = False Negatives (missed deformations)
Precision quantifies the fraction of predicted "Yes" (deformation) true cases:

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

Recall reflects the model's ability to identify all actual "Yes" cases:

$$Recall = \frac{TP}{TP + FN} \quad (15)$$

F1-Score, the harmonic mean of precision and recall, offers a balanced view:

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (16)$$

MCC computes the quality of binary and multiclass classifications by considering true and false positives and negatives, providing a balanced score even with imbalanced datasets.

$$MCC = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (17)$$

These metrics provide a comprehensive view of model performance in predicting deformation risks.

2.6 Real-time prediction and control

The trained model is deployed for real-time prediction during CNC operations. When a novel machining configuration is initiated, the input values are first processed (encoded and normalized) as per training routines. The model then generates an output probability$\hat{y}$. If $\hat{y} > 0.5$, the system flags a high deformation risk. In such cases, immediate corrective actions are triggered by predefined control logic. For instance, a high-risk flag prompts a 10% reduction in cutting speed, utilizing the formula:

$$New\ Cutting\ Speed = Old\ Cutting\ Speed \times 0.9 \quad (18)$$

Where:
"Old Cutting Speed" = initial programmed cutting speed
"New Cutting Speed" = adjusted speed to reduce stress on the workpiece

This reduction reduces both mechanical and thermal stress on the workpiece. Other adaptive responses, like increasing coolant flow or decreasing feed rate, are implemented concurrently based on the material type and observed vibration. If the expected risk is low, the machining operation continues without intervention, ensuring efficiency while maintaining safety.

2.7 Feedback loop and online learning

Following each machining operation, the actual deformation outcome is recorded and compared to the model's prediction. This creates a feedback loop, increasing the model's adaptability over time. Using online learning, the model gradually updates its weights using recent prediction errors. The update rule is given by:

$$w_{new} = w_{old} + \alpha.(y - \hat{y}).x \quad (19)$$

Where:
w_{old}= previous weight
w_{new}= updated weight
α = online learning rate (a small constant)
y = actual label (0 or 1)
$\hat{y}$= predicted output
x = input feature value.

In a feedback-driven online learning system, predictions consistently impact control actions, which then change future input data. This feedback can exacerbate problems if not adequately stabilized. A diminutive learning rate (α) guarantees more gradual weight adjustments and contributes to stability preservation. An elevated learning rate (α) may induce oscillations or divergence, particularly in feedback systems. As updates rely on prediction error, significant spikes in error can disrupt learning until addressed. In practical CNC machining, complete convergence is uncommon. In online learning, weights are adjusted following each data point or small batch, resulting in continual retraining. Periodic full model resets or reinitializations may be conducted to prevent drift or overfitting.

This type of incremental learning ensures that the model evolves with real-world data, adapting to unknown materials, dynamic wear conditions, or unexpected operational disruptions. By combining real-time prediction with continuous learning, the system grows more robust and context-aware over time, eventually achieving a self-improving CNC control mechanism that maximizes machining precision while reducing the risk of costly defects.

The NeuroPID-CNC algorithm represents an intelligent, lightweight, and adaptable solution for predicting and suppressing deformation during CNC machining. It tightly integrates machine learning principles with control engineering strategies using a single-neuron PID-inspired structure, strong preprocessing, accurate prediction, and dynamic feedback adaptation. With ten foundational equations, this system creates a rigorous yet practical framework for real-time decision-making and long-term improvement. The result is a smarter, more efficient, and resilient manufacturing environment.

3 Results

3.1 Experimental setup

All experiments were carried out on a Windows 11 system running Python 3.10. The machine was equipped with an Intel Core i7 processor and 16 GB of RAM. TensorFlow, Scikit-learn, Pandas, NumPy, and Matplotlib were used to train, evaluate, and visualize models. The dataset was divided into two sets: training (70%) and testing (30%). Early stopping and adaptive learning rate scheduling were used to prevent overfitting and speed up convergence.

3.2 Comparison results

Table 2 compares the classification models used on the CNC-DeformControl dataset, including SVM, Random Forest (RF), KNN, Logistic Regression (LR), and the proposed NeuroPID-CNC model.

Table 2: Performance comparison of classification models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC
SVM	88.43	86.22	85.13	85.67	0.76
Random Forest	90.12	89.05	87.60	88.32	0.79
KNN	87.30	84.95	84.00	84.47	0.74
Logistic Regression	86.75	83.90	83.10	83.50	0.72
NeuroPID-CNC	92.00	90.00	93.00	91.50	0.84

The proposed NeuroPID-CNC algorithm had the best performance across all metrics tested. It enables real-time feedback adaptation and improved learning of deformation-prone patterns. This architecture is extremely responsive to subtle patterns in deformation-prone conditions, resulting in higher prediction accuracy and robustness. Furthermore, its streamlined structure minimizes overfitting, whereas more complex models may require deeper tuning. Figure 3 shows the confusion matrix for proposed approach.

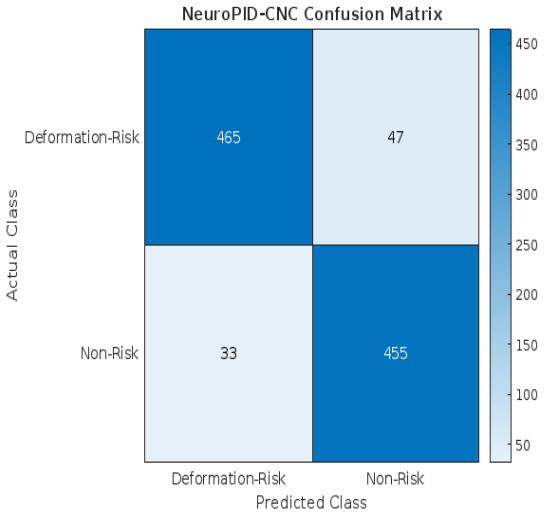

Figure 3: Confusion Matrix for proposed approach

Figure 4 demonstrates that the proposed NeuroPID-CNC model attains the highest accuracy among all evaluated classifiers, reaching 92%.

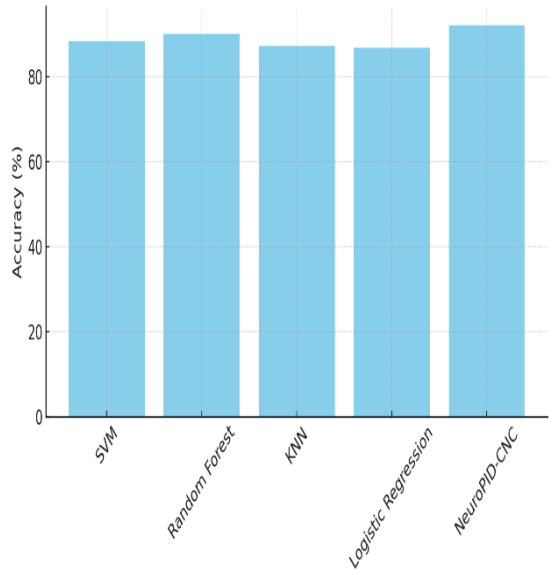

Figure 4: Accuracy comparison

From figure 4, the accuracy of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 4.03%, 2.09%, 5.38% and 6.05% respectively.

This high accuracy demonstrates the model's overall predictive power in correctly identifying deformation risk ("Yes") and non-risk ("No") instances.

The superior performance is due to the unique integration of a PID-inspired control mechanism within the neuron, which allows the model to adjust its internal weights with greater precision during training. This reduces classification errors and improves robustness when dealing with complex interactions between CNC parameters like cutting speed, tool wear, and thermal readings. The model's ability to learn consistently across diverse inputs supports its use in real-time industrial settings. In Figure 5, NeuroPID-CNC leads with a precision of 90%, indicating that it correctly predicts a deformation risk 90% of the time.

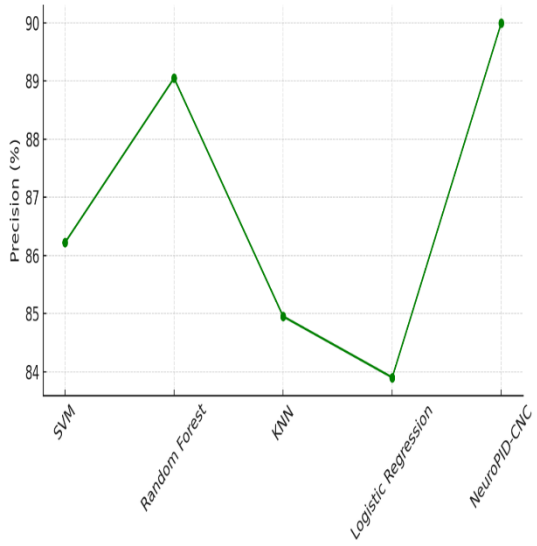

Figure 5: Precision comparison

From figure 5, the precision of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 4.38%, 1.07%, 5.94% and 7.27% respectively.

High precision is required in CNC machining environments to avoid unnecessary operational adjustments caused by false positives. The model's low false alarm rate leads to increased operational efficiency by ensuring that control recommendations (such as reducing cutting speed or increasing coolant flow) are only implemented when there is a genuine risk. This precision advantage stems primarily from the model's ability to learn subtle patterns associated with actual deformation-inducing conditions while filtering out noise from non-critical anomalies. Figure 6 shows that NeuroPID-CNC has the highest recall value of 93%, indicating an excellent sensitivity to actual deformation occurrences.

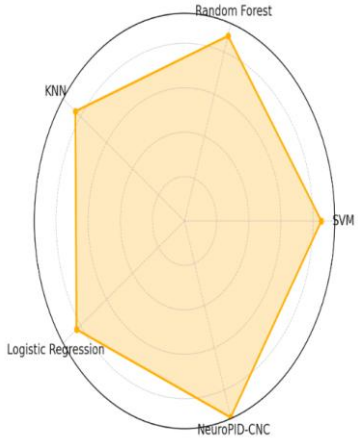

Figure 6: Recall comparison

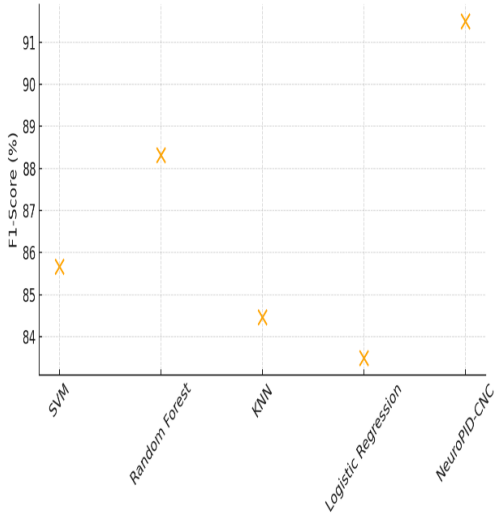

Figure 7: F1-Score comparison

From figure 6, the recall of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 9.24%, 6.16%, 10.71% and 11.91% respectively.

A high recall ensures that the model rarely overlooks true positive cases—an important feature in critical manufacturing scenarios where undetected deformations could jeopardize product quality, damage tools, or cause production downtime. This exceptional recall is due to the model's continuous feedback adjustment loop, inspired by the integral component of PID control, which improves detection sensitivity over time as more real-world machining data is processed. Figure 7 shows that NeuroPID-CNC has the best trade-off between precision and recall among all tested models, with an F1-score of 91.5%.

From figure 7, the F1-Score of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 6.81%, 3.60%, 8.32% and 9.58% respectively.

The F1-score, which is the harmonic mean of precision and recall, measures the model's overall effectiveness in handling the binary classification task. This balanced performance indicates that the NeuroPID-CNC model optimizes both false positives and false negatives, rather than favoring one over the other. Such a balance is critical in industrial settings where both unnecessary interventions and missed deformation risks have financial and operational implications. Finally, Figure 8 demonstrates that NeuroPID-CNC obtained the highest Matthews Correlation Coefficient (MCC) score of 0.84, which is widely considered one of the most reliable metrics for evaluating binary classifiers, especially on imbalanced datasets.

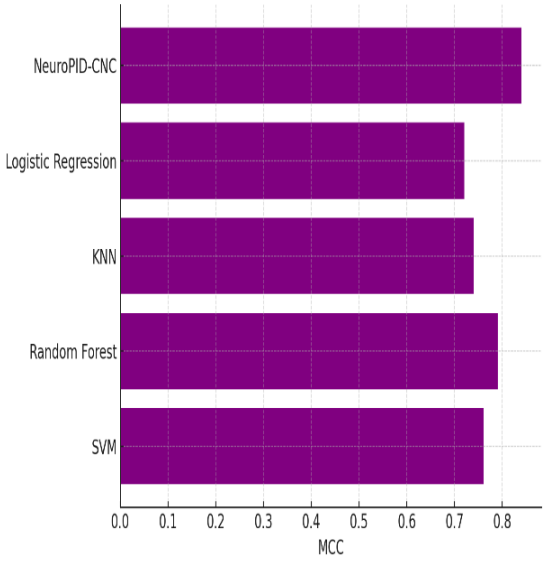

Figure 8: MCC comparison

From figure 8, the MCC of proposed NeuroPID-CNC approach outperforms SVM, RF, KNN and LR by 10.53%, 6.33%, 13.51% and 16.67% respectively.

MCC accounts for all four confusion matrix components (true positives, true negatives, false positives, and false negatives), providing a more complete picture of model performance. The high MCC score confirms that the model consistently and strongly correlates predicted and actual outcomes, regardless of class imbalance. This robust performance ensures reliability and fairness in prediction decisions over varying dataset distributions and machining conditions.

McNemar's test was employed to statistically validate the performance differences across classifiers based on the paired predictions of all models. Table 3 presents the results of the statistical significance test conducted with McNemar's test. The suggested method demonstrated statistically significant superiority over RF ($p < 0.001$), SVM ($p < 0.003$), KNN ($p=0.004$), and LR ($p<0.005$).

Table 3: Statistical Test - McNemar's Test

Algorithm	**McNemar's statistic**	**p-value**
SVM	42.13	0.002
RF	45.24	0.0001
KNN	39.18	0.004
LR	37.89	0.0045

4 Discussion

The single-neuron PID-inspired predictive control technique can surpass machine learning models such as RF, SVM, KNN, and LR. Single-neuron PID-inspired controllers are designed for dynamic system regulation, combining the advantages of PID control with adaptive features. It can adjust weights in real-time utilizing straightforward learning algorithms, rendering it suitable for dynamic, non-linear systems with fluctuating conditions. It provides a temporal viewpoint by evaluating past errors, the current state, and anticipated future behavior, which is consistent with control system needs. The methodology is interpretable, and its performance can be adjusted using domain expertise (e.g., calibrating proportional, integral, and derivative influences).

Machine learning algorithms are models trained in batches. They do not readily adapt in real time without expensive retraining. These are computationally intensive, perhaps rendering them unsuitable for real-time embedded control systems. It does not inherently manage temporal dynamics until augmented by time-lagged features, which may still lack responsiveness or interpretability.

The Single-Neuron PID-Inspired Control is proficient in real-time management of dynamic, nonlinear systems, adaptive error learning, feedback-based decision-making, and resource-constrained applications. The machine learning models exhibit challenges due to inadequate temporal feedback management, rigidity in online learning, elevated computational expenses (particularly in random forests and k-nearest neighbors), and limited adaptability in non-stationary control contexts.

The results demonstrate the superiority of the proposed NeuroPID-CNC model in predicting deformation risk during CNC machining. The model's PID-inspired single-neuron architecture not only provides superior performance across all standard classification metrics but it also ensures operational interpretability and real-time adaptability. These benefits make it an ideal candidate for smart manufacturing environments where precision, dependability, and responsiveness are crucial. Future research will concentrate on implementing the model on industrial edge devices for real-time inference, utilizing multi-modal sensor data including audio and thermal images, applying transfer learning for enhanced generalization, incorporating explainable AI methodologies to augment interpretability, and embedding the model within closed-loop control systems for autonomous CNC parameter modification based on predictive feedback.

5 Conclusion

This study described the NeuroPID-CNC algorithm, which is a lightweight single-neuron PID-inspired classifier for predicting deformation risk in CNC machining. The model outperformed traditional classifiers, achieving the highest accuracy, precision, recall, F1-score, and MCC, proving its suitability for real-time deformation risk detection and adaptive control in manufacturing. The current model was trained using data from a controlled lab environment, which may limit its applicability to different machine types and unstructured production scenarios. It also focuses solely on binary classification and requires manual feature selection, with no support for multi-output or continuous prediction tasks. Future research will focus on deploying the model on industrial edge devices for real-time inference, incorporating multi-modal sensor data such as audio and thermal images, using transfer learning for broader generalization, integrating explainable AI techniques to improve interpretability, and embedding the model into closed-loop control systems for autonomous CNC parameter adjustment based on predictive feedback.

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An Enhanced FSO-BPNN Framework for Anomaly Detection and Early Warning in Power System Monitoring

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Keywords: anomaly detection (AD), internet of things (IOT), monitoring, neural network, power system (PS) smart grid, predictive maintenance

Recieved: May 7, 2025

The increasing complexity of contemporary power networks necessitates the development of enhanced early warning systems and intelligent monitoring to ensure stability and operational efficiency. Traditional approaches to risk prevention and predictive maintenance often fail due to limitations in identifying real-time abnormalities and adapting to dynamic system characteristics. To address these issues, the present research proposes an improved fish swarm optimization with Backpropagation Neural Network (IFSO-BPNN) for anomaly detection (AD) and fault detection (FD) early warning in power system (PS) monitoring that integrates an IFSO algorithm with a BPNN. The major goal is to increase the accuracy of AD and FD in smart grids by utilizing deep learning (DL) and optimization approaches. The IFSO method integrates adaptive weighting and behavioral dynamics into classic fish swarm optimization, improving overall search capabilities. By tweaking BPNN parameters using IFSO, the model achieves higher convergence rates and improved classification accuracy. The assessment dataset was compiled usingInternet of Things (IoT) sensors and pan/tilt camera-based surveillance systems at Beijing power plants, with preprocessing techniques such as min-max normalization and feature extraction using Independent Component Analysis (ICA) to improve model performance. Resultsfrom experiments show that the IFSO-BPNN model outperforms standard algorithms with an accuracy ofFD99.98% and AD 0.9980. These findings illustrate the system's capacity to detect anomalies quickly and perform preventive maintenance. The proposed method, which combines swarm intelligence with neural networks, helps to construct smarter, more robust power grids capable of meeting future energy demands with lower failure risks.

Povzetek: Za odkrivanje napak (FD) in nepravilnosti (AD) v nadzoru elektroenergetskega sistema je razvit IFSO-BPNN (Izboljšana optimizacija jata rib in BPNN). Model izboljša kvaliteto z optimizacijo parametrov BPNN z IFSO, kar omogoča hitro zgodnje opozarjanje in prediktivno vzdrževanje.

1 Introduction

Artificial intelligence (AI), big data, and deep learning (DL) revolutionize power systems (PS) by enhancing feature modeling, control, and fault diagnosis; these are presenting recent advances and applications in monitoring and performance analysis [1]. The expansion ofPS is hindered by growing power demand and environmental objectives, which present challenges for transmission capacity and distance. Advanced, sustainable energy solutions are being used to achieve carbon peaking and neutrality [2].Reconstruction errors and thresholding are used in AD(AD) to minimize false alarms and isolate fault areas by training a model to learn typical system behaviorin an unsupervised manner [3].Approximately 70% of energy is produced by thermal power plants; new large-capacity units (600–1000+ MW) improve operating efficiency but make system coupling and integration more difficult [4].Real-time data collection and analysis of electrical characteristics is part of PS monitoring, used to ensure system stability, identify problems, improve performance, and assist in decision-making for dependable and effective power grid operation [5].As demonstrated by the arctic sky tragedy, the expansion of the cruise industry needs advanced, dependable PS to avoid blackouts, which endanger public safety, the environment, financial stability, and reputation [6].Potential false alarms, reliance on data quality, difficulty identifying new abnormalities, computational complexity, difficulties with real-time implementation, and threshold setting are some drawbacks of AD and early warning in PS [7].

1.1 Aim and contribution of the research

The aim of the research is to develop a new method, improved fish swarm optimization with Backpropagation Neural Network (IFSO-BPNN), for detecting anomalies and faultsin PS by integrating BPNN and IFSO algorithms. The goal is to increase the accuracy and efficiency of AD and fault detection (FD) in smart grids while also enabling proactive maintenance. The research's key contributions include the following:

- ***IFSO Algorithm***: Improves the global search capability and adaptive weighting of classic Fish Swarm Optimization, resulting in less convergence time and higher classification accuracy in anomaly and fault identification.
- ***BPNN Optimization***: IFSO is used to optimize BPNN parameters, which results in quicker convergence and greater classification accuracy for real-time AD and FD.
- ***Advanced-Data Preprocessing:*** Uses min-max normalization and Independent Component Analysis (ICA) for feature extraction, improving the model's performance in power system monitoring by efficiently preprocessing Internet of Things (IoT) sensor and surveillance system data.

The next phase (phase 2) clearly explains the existing research about ADand early warning in PS monitoring. Phase 3 presents the methodology, Phase 4 provides the result and discussion of existing vs proposed method, and Phase 5 deliversthe conclusion.

2 Related works

The aim of the research [8] was to increase the dependability of seismic stations. For reliable power failure prediction, the SeismoGuard Ensemble, which comprises random forest (RF), support vector machine (SVM), k-nearest neighbors (KNN), and logistic regression (LR), along with IoT monitoring, was used. Results demonstrate that the approach attained 90% accuracy and increased dependability. The dataset's reach was restricted; however, the data contains long-term testing with wider generalization across various situations. A combination of elliptic curve cryptography (ECC)-based token control with deep reinforcement learning (DRL)-based sleep scheduling was used for secure and adaptive power management under possible threat conditions in order to improve the security and energy efficiency of wireless sensor networks (WSNs) [9]. The approach achieved a 15% increase in energy efficiency and a 20.01% power reduction. While simulation-based outcomes were validated, more verification was required for scalability and real-world implementation under various attack types.

Following data cleaning and feature extraction, supervisory control and data acquisition (SCADA)were processed using aConvolutional neural network - bidirectional gated recurrent unit (CNN-BiGRU) with attention to identify wind turbine faults [10]. Accurate FD in actual wind farms was accomplished; however, it was constrained by the generalizability of the data source and the possibility of overfitting to particular turbine models.
The monitoring of wind turbine health was enhanced by utilizing mutual information to determine essential parameters, support vector regression (SVR) for thresholding, and long short-term memory -autoencoder (LSTM-AE) for AD [11]. The outcome demonstrated precise AD and successful identification of crucial parameters. Real-time monitoring settings could show a decline in performance due to noisy data or inadequate temporal information. To optimize the monitoring and security of smart hospitals, machine learning (ML) and edge-based advertising on Contiki Coojawere applied to identify IoT network intrusions and e-health incidents [12]. The system was successful in identifying cyberattacks and e-health events, but it was very dependent on the reality of the simulated data, which could not work effectively with complex or novel attack patterns.
Abnormalities in wind turbines were discovered and accurately analyzedutilizing a combination of methods. Local outlier factor (LOF) and adaptive K-means for preprocessing, Extreme Gradient Boosting (XGBoost) for diagnosis, and long short-term memory-stacked denoising autoencoder (LSTM-SDAE) for feature extractionwere employed [13]. The technique increased wind turbine dependability by efficiently identifying and diagnosing problems in real-time utilizing SCADA data. Performance was dependent on the caliber of preprocessing and could be hampered by noisy data or hidden anomalies. The research created an early warning system that incorporates meteorological data to enhance PS dependability and proactively reduce atmospheric dangers [14]. The technology enhanced defect detection and prevented outages during severe weather; however, its performance depended on data quality and erratic weather patterns. The advancements in battery electric vehicle (BEV) technology, platforms, charging, and monitoring were examined to address issues regarding safety, charging, and range in new energy cars [15]. Although cutting-edge platforms and safety features dominate the BEV industry, however, there were issues with battery lifecycle safety, charging simplicity, and weather adaptation. The PS load margin was determined by utilizing an artificial neural network (ANN) trained on phasor measurement unit (PMU) data and model simulations to ensure voltage and small-signal stability [16]. An ANN's ability to anticipate load margin effectively cannot exceed a dependence on the quality of PMU data and model assumptions in actual systems. To increase safety in nuclear-powered marine

operations, developments in ship nuclear power machinery (SNPM) design, fault diagnostics, and risk assessmentwere evaluated [17]. Design enhancements and investigation spaces were identified, and an integrated risk framework was suggested; however, knowledge remains limited and needs to be verified. Table 1 provides the related works summary table.

Table 1: Comparative Summary of the related works

Reference	**Methods**	**Results**	**Limitations**
Duet al. [8]	SeismoGuard Ensemble (RF, SVM, KNN, LR) + IoT monitoring	Achieved 90% accuracy, improved dependability of seismic stations	Limited dataset coverage; needs generalization and broader testing
Qinet al.[9]	ECC token control + DRL-based sleep scheduling for WSN	15% energy efficiency gain, 20.01% power reduction	Simulation-based only; real-world scalability and threat resilience not verified
Xianget al.[10]	SCADA data + CNN-BiGRU + attention mechanism	Accurate wind turbine FD in real wind farms	Data source generalizability is limited; overfitting risk to specific turbine models
Chen et al. [11]	Mutual information + SVR for thresholds + LSTM-AE for anomaly detection	Accurate anomaly detection; key parameters identified	Real-time performance could degrade under noisy or incomplete data
Said et al. [12]	ML + edge-based intrusion detection on Contiki Cooja for smart hospitals	Identified e-health events and IoT network intrusions accurately	Simulated data could fail under real, complex attack patterns
Zhang et al. [13]	LOF + adaptive K-means preprocessing + XGBoost + LSTM-SDAE	Real-time, accurate ADand diagnosis in wind turbines	Sensitive to data quality; hidden anomaly types may be missed
Božičeket al.[14]	Early warning system using meteorological data	Prevented outages and improved detection during extreme weather	Dependent on weather unpredictability and data quality
He et al. [15]	BEV platform, charging/swapping stations, and monitoring platform	Technological dominance and safety improvements in the BEV market	Issues remain in battery safety, weather adaptability, and charging ease
Bento et al. [16]	ANN trained on PMU data + model-based simulation	Accurate load margin prediction ensuring voltage and small-signal stability	Performance hinges on PMU data and assumptions in simulation models
Adumene et al. [17]	SNPM designs + fault diagnosis + risk assessment	hybrid risk framework; identified design progress	Incomplete knowledge base; needs validation and framework integration

2.1 Research gap

The method additionally solves past techniques' drawbacks, such as restricted data generalization, overfitting, simulation reliance, and data quality sensitivity. The proposed approach, IFSO-BPNN, provides a scalable, real-time solution for proactive maintenance and problem detection in complex, large-scale power networks. The research fills a gap by merging an IFSO method with a BPNN for PS anomaly and fault identification. Compared to earlier techniques, this approach improves accuracy, convergence speed, and FD resilience, especially in noisy situations.

3 Research methodology

This section discusses IoT sensor-based data collection in PS and introduces the IFSO-BPNN approach for anomaly and fault identification, as well as early warning in PS monitoring. Figure 1 shows the methodology flow, which includes data pretreatment, feature extraction, and model optimization.

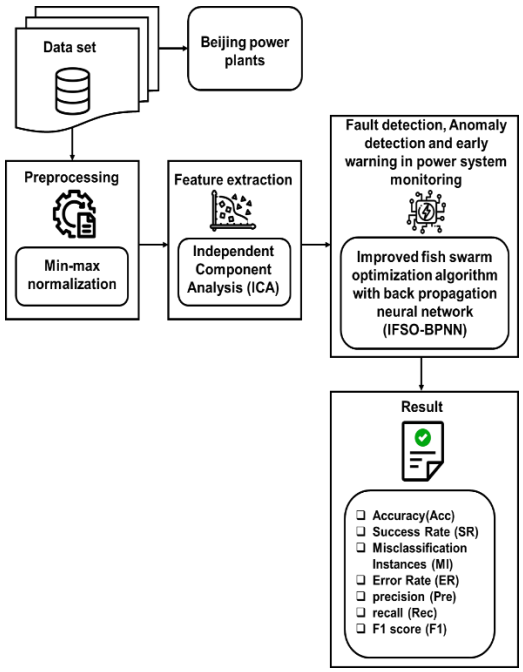

Figure 1: Flow of the proposed method

3.1 Data collection

The system configuration includes a pan/tilt integrated camera, a series of local storage DVR hosts, a 1-terabyte dedicated hard disk, and equipment from major domestic video equipment manufacturers. A wireless networking module is an important element that allows direct connection across 4G or 5G wireless networks. The research is centered on power stations surrounding Beijing, where the distribution stations lack wired networks and must communicate over wireless networks. To achieve that, on-site terminal equipment is required to access different network types at the distribution station, such as 2G/3G/4G, GSM, CDMA, and wired networks. Many of these stations are found in basements. In the event of a severed wireless connection between the station and the platform, short messages transmitted to the terminal equipment at the distribution station allow for simple permission and re-establishment of communication. The data were split into an 8:2 ratio, 80% for training, and 20% for testing dataset.

3.2 Data preprocessing via min-max normalization

Min-max normalization is a common method used for numerical sensor and camera data from Beijing power plants to scale characteristics between 0 and 1, in which the values of a feature are translated into a preset range, usually [0-1]. The method retains data connections, hence being suitable for a wide range of ML applications. The transformation is carried out using the following Equation (1).

$$X_{new} = \frac{x=min}{max(x)-min(x)} \quad (1)$$

X_{new} = The adjusted value obtained after scaling the data X = outdated value, $max(x)$= dataset's highest possible value.$min(x)$ = dataset's lowest possible value. The normalizing technique improves AD and FD in PS monitoring by ensuring that all data points have a consistent scale, which increases predictive model accuracy.

3.3 Feature extraction using independent component analysis (ICA)

ICA is a current statistical technique that attempts to break down observable data into statistically independent components. The ICA was used on sensor and surveillance data to reduce dimensionality and extract essential features, which improved the IFSO-BPNN model's capacity to detect abnormalities in PS monitoring as a linear mixture of independent components, expressed as follows in Equation (2).

$$y = B.T \quad (2)$$

Where: y represents the observed data vector, Bdenotes the mixing matrix, and T denotes the separate components. In ICA, components are assumed to be statistically independent and non-Gaussian, with a square and unknown mixing matrix$B$. To extract the components, calculate the inverse X of matrix B as follows in Equation (3).

$$T = X.y \quad (3)$$

ICA divides data into statistically independent components, helping in AD and FD in PS. While the technique does not give direct variance or ordered data, the enhanced sparsity-based technique improves feature extraction and speeds up convergence for real-time applications such as early warning systems. ICA has been widely applied in disciplines like face recognition and dimensionality reduction. PS monitoring, which extracts essential characteristics from sensor data, catches

complicated, non-Gaussian patterns that standard approaches typically overlook, resulting in improved AD, FD and maintenance efficiency.

3.4 Detection and early warning in PS monitoring using improved fish swarm optimization with backpropagation neural network (IFSO-BPNN)

The IFSO-BPNN enhances AD and FD in PSby optimizing BPNN parameters with the IFSO algorithm, increasing classification accuracy, and allowing for real-time predictive maintenance. Figure 2 displays the proposed method's flow diagram for power system monitoring.

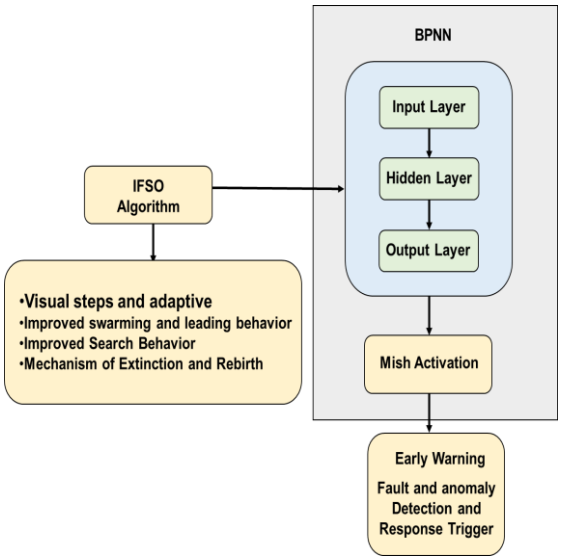

Figure 2: Flow diagram for the proposed method.

3.4.1 Back-propagation neural network (BPNN)

The BPNN is a multi-layer feed-forward artificial neural network designed to identify anomalies in PS. The architecture consists of an input layer, one or more hidden layers, and an output layer. Sensor readings, system performance measurements, and ambient parameters are all sent into the input layer. The hidden layers discover complicated patterns in the data, whereas the output layer anticipates anomalies and faults such as system malfunctions or failures. Each neuron's output is defined by applying an activation function to the weighted sum of inputs in Equation (4).

$$x = \sum_{j=1}^{n} z_j . y_i + a \qquad (4)$$

Where $y_i$is the input, $z_j$is the weight, $a$is the bias, and σ (·) is the exponential activation function (TanhExp) $f(x) = x.\tanh(e^x)$, generally mish activation function $tanh$. The Mish function is smooth and comparable to TanhExp. The formula is provided as follows. $F(x)x.tanh(softplus(x))$. where softplus function$f(x) = \log(1 + e^x)$.Mish is a self-regulatory activation that improves accuracy and generalization instead of standard function. The process is smooth and non-monotonic, allowing for modest negative outputs while retaining strong positive flow, avoiding problems like dead neurons in ReLU.x: Input to the neuron. $Soft\ plus$ (x): A smooth variant of ReLU.$tanh(\cdot)$: Implements smooth limiting behavior for high input values. Data from the power system is collected, standardized, and sent to the network for training. Normalization guarantees that each input feature contributes evenly to model training. During forward propagation, input data is transferred through the layers as the model produces predictions. Backpropagation then changes the weights and biases depending on the loss function, which is commonly Mean Squared Error (MSE) and computed as follows in Equation (5).

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(x_{pred} - x_{actual}\right)^2 \qquad (5)$$

To improve the model's capacity to detect anomalies and fault, increase system dependability, and provide early alerts for proactive PS repair.

Loss function:

In the PS anomaly and fault detection, the loss function is critical for reducing prediction errors and improving model parameters. The BPNN's output layer computes the error between the expected output and the actual observed detection using the MSE and an appropriate activation function. The error gradient of each neuron in the output layer could be computed as follows in Equation (6).

$$\delta_{out} = \left(x_{pred} - x_{true}\right).\sigma'(w) \qquad (6)$$

x_{pred} : predicted output (anomaly, and fault score). x_{true}: True label (0 for no abnormality and 1 for anomaly). $\sigma'(w)$ is the derivative of the activation function for the neuron's input w.The gradient of the hidden layers is affected primarily by the output error, but also by the gradients of the following layers. The gradient of a hidden layer neuron G_j could be calculated using the chain rule in Equation (7).

$$\delta_{hidden} = \sum_i z_{j.i}.\delta_i.\sigma'(w_j) \qquad (7)$$

δ_{hidden}: Error gradient for a hidden layer neuron. $z_{j.i}$: Weight coupling hidden layer cell G_j with output neurons. δ_i: The error gradient of the output neuron.$\sigma'(w_j)$: Derivative of the activation function for the buried layer input w_j.Gradient descent is used to update weights and biases during training to minimize the loss function. The rules for updating the weights (z) and biases (a) in each round are as follows in Equations (8-9).

$$z^{(n+1)} = z^{(n)} - \eta.\frac{\partial P}{\partial z} \quad (8)$$

$$a^{(n+1)} = a^{(n)} - \eta.\frac{\partial P}{\partial a} \quad (9)$$

The current weights and biases at iteration n are denoted by $z^{(n)}$and$a^{(n)}$. The learning rate (η) is a hyperparameter that controls the step size. The gradients of the loss function about weights and biases are $\partial\frac{\partial P}{\partial z}and\frac{\partial P}{\partial a}$, respectively. The learning rate η adjusts the model's weights and biases to reduce prediction errors for ADinPS.

3.4.2 Improved fish swarm optimization (IFSO)

FSO was selected over PSO, GA, and DE because of its greater global search capabilities and adaptive behavior, which improve convergence and classification accuracy in AD and FD. An IFSO is proposed to increase detection accuracy and convergence speed. For balanced exploration and exploitation, the system incorporates adaptive control overstep size and visual field, which shrinks with iterations. By eliminating default search behaviors and crowding conditions, swarming and following techniques are improved. Fish retry with modified settings when an improved solution is discovered. To preserve the quality of global optimization, an extinction-regeneration system removes the most susceptible fish and replaces it with a more suitable one. This improved method efficiently optimizes BPNN parameters for AD and FD in PS.

The classic Fish Swarm Algorithm (FSA) has fixed visual and step sizes, which can hinder convergence. To improve AD performance, an adaptive piecewise function is proposed to gradually decrease visual and step sizes with iterations, finding a balance between speed and accuracy. StepSS $(iter)$ and adaptive $V(iter)$ are defined as follows in Equations (10-11).

$$V(iter) = \text{int}\left(max_v \times \left(\frac{\log(min_v/max_v)}{\log(max_{gen})}\right)^{iter}\right) \quad (10)$$

$$SS(iter) = \text{int}\left(max_s \times \left(\frac{\log(min_s/max_s)}{\log(max_{gen})}\right)^{iter}\right) \quad (11)$$

$V(iter)$: The artificial fish's field of vision at iteration iter. $SS(iter)$: The maximum step the fish can take during iteration. max_v: Step size and initial (maximum) visual range. min_v: The smallest step size and visual range for efficient searching. The maximum number of iterations ismax_{gen}. $iter$: The number of the current iteration. For discrete issues, $int(\dots)$ rounds values to integers. Values are rounded to integers, with a minimum step and visual sizes set to 1 for discrete issues such as attribute reduction in Equations (10-11); both the visual and step sizes use an exponential decrease from maximum to minimum across iterations, allowing for quick global search at the beginning and accurate local search at the final stage. The provided AD, and FD framework's convergence and detection accuracy are enhanced by the adaptive technique.

The artificial fish swarm algorithm (AFSA) uses swarming and following behaviors to determine convergence speed. However, narrow distances can cause local optima and delayed convergence. Randomization changes swimming's step size to prevent premature convergence. The algorithm focuses on determining the optimal position of fake fish for efficient attribute reduction, and eliminates search behavior to save execution time. The enhanced swarming and subsequent behaviors are defined as Equations (12-13).

$$Y_{next} = Y_j + step \times (Y_d - Y_j) if\ G(Y_d) > G(Y_j) \quad (12)$$

$$Y_j = Y_d\ if\ G(Y_d) > G(Y_j) \quad (13)$$

Y_{next}: The fake fish's next position.Y_j: The fake fish's current location.Y_d: The position of the swarm's center.$step$: The step size for movement is determined by a random component. $G(Y_d)$: The fitness value at the center position. $G(Y_j)$: The fish's fitness value at that present location. These changes improve the algorithm's efficiency, resulting in faster convergence and higher performance.

Improved Search Behavior**:** In the AFSA, searching for behavior entails exploring the available domain to discover alternatives. The number of tries has a significant impact on search efficiency, frequently resulting in premature or inefficient searches. To solve these things, extend the viewing field when no superior location is discovered after a certain number of difficulties. When a suitable place is located, the fish takes one step towards that, with a maximum step size of $step_{new} = 2 \times step$. Without false, the fish moves randomly. IFSO's capacity was improved to efficiently tune BPNN parameters, hence increasing accuracy and convergence in PS anomaly and fault detection.

Mechanism of Extinction and Rebirth: The algorithm uses an extinction mechanism to remove the least suitable fish, enhancing swarm adaptability but decreasing swarm size and randomness. A regeneration mechanism is then included to restore swarm size by regenerating highly adaptable fish, ensuring resilience and enhancing efficiency by shortening iteration durations while maintaining high fitness levels. The IFSO-BPNN approach attempts to discover and detect deviations in PSmore efficiently by optimizing neural network parameters, assuring faster convergence, and improving prediction accuracy for proactive maintenance. Algorithm 1 displays IFSO-BPNN.

Algorithm 1: IFSO-BPNN

Step 1: Initialize the BPNN parameters
Initialize BPNN with input layer, hidden layers, and output layer
Set learning rate η and number of iterations max_iter
Step 2: Initialize the Fish Swarm Optimization (IFSO) parameters
Initialize fish swarm population size, maximum visual field (max_v), and step size (max_s)
Set the minimum values for visual field (min_v) and step size (min_s)
Step 3: Data Preprocessing
Preprocess data:
  Normalize sensor readings using min-max normalization
  Perform feature extraction using Independent Component Analysis (ICA)
Step 4: Training the BPNN with IFSO optimization
for each iteration in range(max_iter):
  for each fish in the swarm:
    visual = V(iter)
    step = SS(iter)
    if G(Y_d) > G(Y_j):
Y_j = Y_d
  for each fish in the swarm:
BPNN.weights = optimize_with_fish_swarm(Y_j)
BPNN.biases = optimize_with_fish_swarm(Y_j)
  for epoch in range(max_epochs):
    output = BPNN.forward(input_data)
    error = calculate_MSE(output, expected_output)
    gradients = backpropagate(error)
BPNN.weights = BPNN.weights - η * gradients.weights
BPNN.biases = BPNN.biases - η * gradients.biases
Step 5: Extinction and Regeneration
remove_weakest_fish()
regenerate_strong_fish()
Step 6: Anomaly and Fault Detection
anomaly_score = BPNN.predict(test_data)
fault_score = BPNN.predict(test_data)
  if anomaly_score> threshold or fault_score> threshold:
trigger_early_warning()
Step 7: Return the optimized BPNN model for PS monitoring
Return BPNN model optimized using IFSO

4 Result and discussion

This section compares the result of the proposed method, an enhanced IFSO-BPNN framework, for AD and FD early warning in PS monitoring with existing methods. The evaluation was conducted using parameters such as accuracy (Acc), success rate (SR), misclassification instances (MI), error rate (ER), precision (Pre), recall (Rec), and F1 score (F1).

4.1 Experimental setup

The IFSO-BPNN technique is implemented on a machine equipped with an Intel i7 CPU, 16GB RAM, and a 512GB SSD. Python 3.9 is used for implementation, including libraries like NumPy, TensorFlow, Scikit-learn, and Matplotlib for processing and visualization. Table 2 displays the hyperparameters of the proposed method.

Table 2: Hyperparametric for proposed method

Hyperparameter	**Range/Value**
BPNN Learning Rate (η)	0.01 to 0.1
Max Iterations (max_iter)	100 to 1000
Swarm Population Size	50 to 200
Max Step Size (max_s)	0.1 to 1.0
Min Step Size (min_s)	0.01 to 0.1
Learning Rate (η) for BPNN	0.001 to 0.01
Fitness Function	Error of BPNN model predictions
MSE Threshold for Convergence	0.001
Activation Function for BPNN	Mish, TanhExp, or ReLU

4.2 Performance outcome

Figures 3 and 4 show the ROC curve and confusion matrix for anomaly detection and fault detection, respectively. The performance was evaluated based on the false positive rate, the true positive rate for the ROC curve, and the predicted and actual for the confusion matrix.

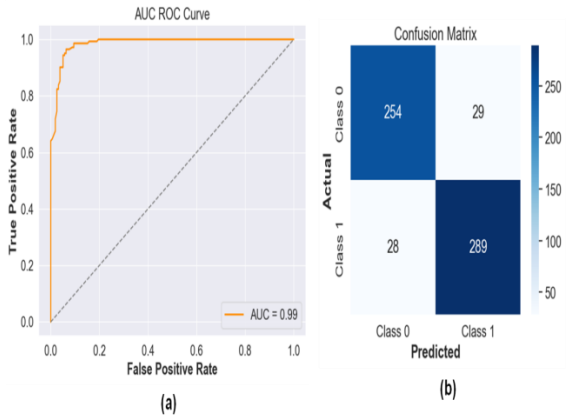

Figure 3: Anomaly detection (a) Roc curve, and (b) confusion matrix.

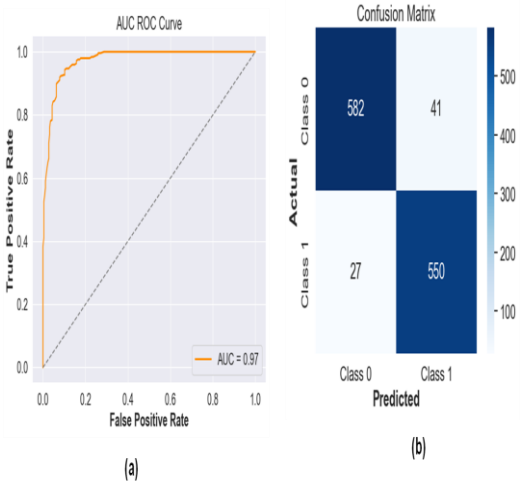

Figure 4: fault detection (a) Roc curve, and (b) confusion matrix.

4.3 Parameter explanation

Accuracy (Acc):Acc is defined as the ratio of accurately predicted occurrences (including true positives and true negatives) to total instances in a dataset, which measures the overall performance of PS monitoring and fault detection.Success rate (SR): The smart grid system is calculated as the proportion of accurately discovered faults and successful predictions to improveFD and maintenance accuracy.Misclassification instances (MI): The events occur when the model incorrectly identifies problems or normal conditions to demonstrate the possible flaws in identifying power defects.Error rate (ER):The fraction of misclassified cases, revealing the model's errors with an emphasis on decreasing mistakes in FD for PS.Precision (Pre) is the fraction of successfully diagnosed errors among all expected anomalies, demonstrating detection accuracy. Recall (Rec) measures the model's ability to detect all real abnormalities. F1 Score (F1) balances precision and recall. These metrics assess the IFSO-BPNN model's ability to accurately detect and monitor PS faults.

4.4 Comparison phase

The proposed method, IFSO-BPNN, is compared to the existing methods like Long Short-Term Memory (LSTM) [18] for FD, k-Nearest Neighbors (KNN), Decision tree classifier (DTC), and Random Forest (RF) [19] for ADand early warning in PS monitoring with evaluation metrics.
Table 3 and Figure 5 (a-b) display the comparison of metric values for the proposed method and existing methods to predict FD and FD in early warning of PS monitoring. The proposed IFSO-BPNN (98.5%) method achieves greater Acc than LSTM (91.21%).

Table 3: FD metrics values for proposed method.

Metrics	LSTM [18]	IFSO-BPNN [Proposed]
Acc (%)	91.21	98.5
SR(%)	92.42	96.85
MI	17	9
ER (%)	8.76	5.15

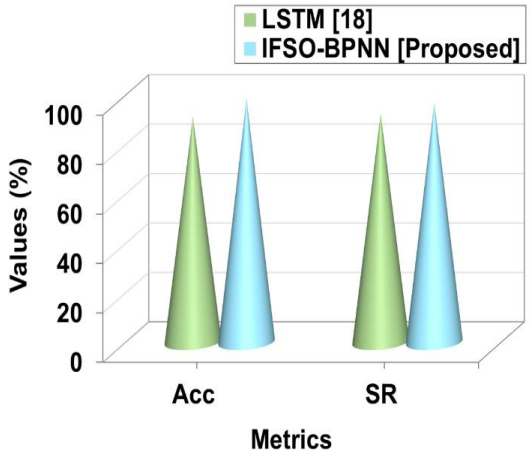

Figure 5(a): Acc and SR value for FD.

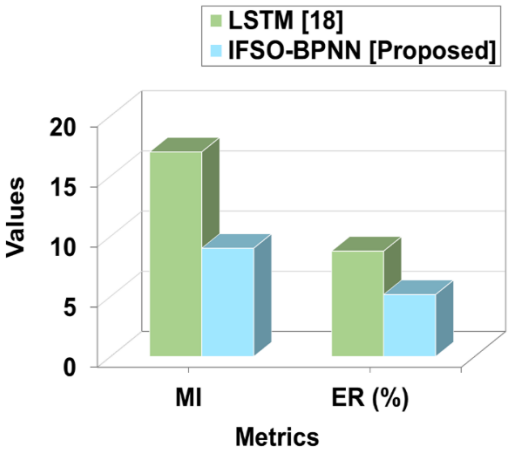

Figure 5(b): MI and ER FD value for proposed method.

Table 4 and Figure 6show the comparison of the proposed method and existing methods to evaluate the metric valuesused to predict ADand early warning of PS monitoring. The proposed IFSO-BPNN (0.9980) method achieves greater Acc than KNN (0.9729), DTC (0.9937) and RF (0.9976).

Table 4: Metrics values for proposed vs existing methods.

Metrics	KNN [19]	DTC [19]	RF [19]	IFSO-BPNN [Proposed]
Pre	0.9732	0.9937	0.9976	0.9978
Rec	0.9729	0.9937	0.9976	0.9977
F1	0.9729	0.9937	0.9976	0.9979
Acc	0.9729	0.9937	0.9976	0.9980

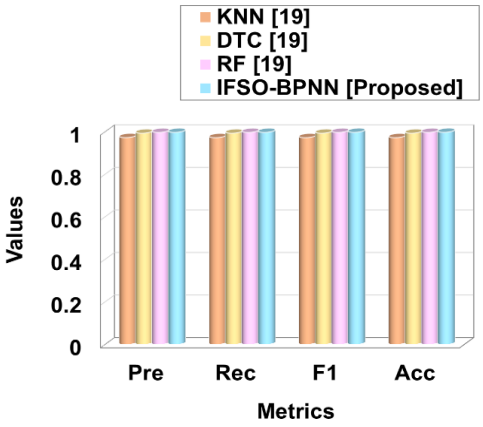

Figure 6: Evaluation metrics values for the proposed method.

In this research, both BPNN and IFSO-BPNN techniques were trained for FD and AD in PS. The numerical results of the ablations study for FD and AD in PS are displayed in Table 5, indicating that IFSO-BPNN performs better than BPNN.

Table 5: Outcome of ablation study

Method	AD Acc (%)	FD Acc (%)
BPNN	98.0	98.2
IFSO-BPNN	99.8	98.5

4.5 Discussion

The proposed IFSO-BPNN method achieves higher Acc, Pre, Rec, F1 and SR and significantly reduces MI and ER compared to existing methods like LSTM, KNN, DTCand RF. Existing models struggle with real-time adaptation and FD accuracy. The IFSO method overcomes these constraints by improving global search and optimizing BPNN parameters for improved performance. The connection helps electricity systems identify faults and provide early warnings. The key benefit is the substantial dependability and precision in predictive maintenance, which improves the robustness and efficiency of PS. Deploying the IFSO-BPNN model in smart grids provides real-time defect detection, such as detecting transformer overheating early on, averting blackouts, lowering maintenance costs, and enhancing energy distribution reliability across locations.

5 Conclusions

The improved early warning model, combining IFO with a BPNN (IFSO-BPNN), was presented to improve FD and predictive maintenance in smart power systems. The method aims to optimize neural network parameters for higher detection accuracy. The results demonstrated exceptional performance with FD accuracy (98.5%) and AD accuracy (0.9980) higher than existing methods. To address statistical validation, the IFSO-BPNN model has limited specificity, required more processing resources, and relied on precise parameter adjustment, which could leave an impact on real-time performance and generalizability across different power systems. The dataset's limited coverage of Beijing's local distribution stations, as well as a lack of sample size and class distribution information, limit its generalizability and model performance assessment. The future scope may extend the dataset to cover varied power systems, and providing precise details on sample size and class distribution would improve model resilience, generalization, and performance evaluation. Future research should focus on increasing specificity, testing in a variety of grid scenarios, and incorporating real-time adaptive processes to widen and improve the system's FD capabilities and use confidence intervals and standard deviations to demonstrate dependability. Future directions include statistical validation methods, such as confidence intervals and standard deviations, to support the reliability of results, providing clearer justification for performance metrics and model robustness. Future work will concentrate on providing thorough feature extraction, dimensionality reduction using ICA, and using correlation reduction methods for better analysis. Future research aims to enhance model performance and generalization by improving feature extraction, incorporating diverse data sources, and reducing dimensionality.

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Automated AutoCAD Drawing Assessment via Image Processing and Vector Transformation Techniques

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Keywords: graphics processing, computer graphics. information extraction, computer graphics examination system, computer-aided design (CAD)

Received: April 28, 2025

Conventional assessment practices in computer graphics courses, particularly those that utilize AutoCAD, often rely on manual grading or basic template-matching strategies. These methods are ineffective and biased, particularly when used for extensive evaluations. Intelligent evaluation methods and automated image processing must be integrated as educational technology continues to evolve. The purpose of the proposed effort is to develop and put into use an intelligent AutoCAD computer drawing evaluation system that uses image processing technologies. Enhancing assessment accuracy, automating scoring, and utilizing robotic technologies to combine virtual drawing analysis and actual drawing validation are the objectives. The system evaluates student drawings using MATLAB-based techniques, including vector transformation, grayscale conversion, binarization, and histogram similarity. It extracts components using DXF file parsing, performs geometric matching, and features extraction. A feedback-driven retransmission method ensures packet correctness. A servo motor-powered drawing computer duplicates input drawings, and performance is assessed using torque analysis, picture entropy, consistency, and smoothness criteria. The system could accurately reproduce student drawings with an accuracy of more than 0.1 cm and an average drawing speed of 1.75 cm/s. The system's dependability was confirmed when evaluation ratings for example drawings nearly matched hand grading. Within the robotic arm's torque limits, moment and motion analysis verified operational safety and accuracy. The proposed approach automates computer graphics analysis by combining hardware and software elements for perceptive evaluation. However, limitations on robot motion and image quality sensitivity were limitations, requiring future improvements.

Povzetek: Predstavljen je inteligentni sistem za avtomatsko ocenjevanje risb AutoCAD z obdelavo slik in vektorsko transformacijo. Uporablja DXF analizo, primerjavo slik in robotsko reprodukcijo za natančno in objektivno ocenjevanje.

1 Introduction

Recent advancements in generative models in language and imaging have transformed the perception of computers as co-creators, enabling creative AI to actively participate in idea exploration [1]. Augmented Reality (AR) enhances learning in graphic design education by providing dynamic, 3D-registered visuals, improving students' practical interaction with intricate mechanical structures and spatial comprehension [2]. AutoCAD is a popular program for creating technical drawings and documentation in design and architecture, but beginners may face challenges due to standardized teaching strategies [3].

Automatic List Processing (AutoLISP), a key component of AutoCAD, is a software development tool that automates various engineering and design processes, despite its high skill and work requirements [4]. Screencasts enhance concurrent learning in CAD-based and technical drawing classes, providing flexible, self-paced learning options for students lacking prior CAD experience and limited curriculum time [5]. Conventional CAD systems enhance manufacturing productivity in industries like metallurgy, glass working, and woodturning by facilitating detailed 3D modeling and group technology for small-batch production [6].

The goal of the research is to create and put into use an intelligent AutoCAD computer drawing evaluation system that uses image processing technologies. Enhancing assessment accuracy, automating scoring, and utilizing robotic technologies to combine virtual drawing analysis and actual drawing validation are the objectives.

- To create an automatic AutoCAD assessment system that combines image processing methods with DXF file structure parsing for precise and impartial grading.
- To use sophisticated vector transformation techniques, like skeleton extraction, binarization, and grayscale conversion, to transform visual drawing inputs into formats that could be analyzed.
- To put into practice a feedback-driven retransmission algorithm that replicates annealing principles for effective drawing packet delivery and correction.
- To create a robotic drawing platform with servo motors that could physically replicate digital inputs, confirming the accuracy of vector interpretations.
- To test mechanical drawing precision and compare automated scores with manual grading to assess the accuracy and dependability of the suggested solution.

System organization: Related research on AutoCAD assessment is reviewed in Section 2. The image processing methods, methodology, and DXF file analysis are explained in Sections 3–5. Results, experiments, and system implementation are presented in Sections 6–11. The investigation is concluded in Section 12, which also suggests potential enhancements for evaluation accuracy and scalability.

2 Related work

Employing task performance metrics and rubric-based imagination evaluation with undergraduate students compare the AutoCAD 2025 and AutoCAD Mechanical 2025 CAD tasks' efficiency and creativity. Efficiency and creativity were increased by AutoCAD Mechanical; however, short-term evaluation, a single discipline focus, and a lack of user input analysis cloud were some of the drawbacks [7]. Create an automated evaluation tool for CAD models in mechanical courses that uses a model-based methodology to assess parametric, feature-based, and geometric aspects with parameterization. Although the CAD Model Automatic Assessment (MAA) Tool efficiently automates model evaluation, limitations include restricted validation across several CAD platforms and reliance on teacher-defined coefficients [8]. Sulfur Hexafluoride (SF6) dial pointer recognition system that is accurate and effective, utilizing Computer Aided eXtended Application (CAXA) secondary development for automated CAD drawing generation, open-source computer vision library (OpenCV)-based angle detection, and socket communication. The method achieved a 0.69° average error, exceeding accuracy requirements; restrictions include dependence on particular applications and restricted adaptability to varying dial designs [9]. Following an experiment with focus groups, a literature-informed questionnaire was given to 59 students and 21 educators to assess preferences between hand drafting and CAD in architectural working drawings. CAD was selected for effectiveness and accuracy; restrictions include interest dependence on duplicate instructions and restricted understanding of context during site visits [10]. To enhance the teaching of cosmetics design by incorporating graphic design software, evaluating efficacy, paintbrush choice, and digital design efficiency through comparative tests, two-stage questionnaires, and expert assessments. Computer drawing reduced design time in half and increased the efficacy of instruction; however, the method had drawbacks, such as a learning curve at first and a dependence on particular software capabilities like symmetry functions [11]. Simple brush painting that is automated and realistic. The approach, which was evaluated on the FaceX dataset using Python and TensorFlow, merges an attention mechanism (AM) with a Long Short-Term Memory (LSTM) network. The model's accuracy was 98.63% and the F1 score was 98.75%; however, that requires a lot of processing power and the outcome could differ depending on the dataset [12]. The computer vision system uses wavelet denoising, multi-feature fusion, transfer of style enhancement, and recognition models trained on WikiArt and OilPainting datasets to classify painting styles and analyze sentiment. The model attained 90% sentiment accuracy and over 95% style classification; however, performance could differ when applied to less structured, real-world artwork that wasn't part of benchmark datasets [13]. Table 1 provides the related works summary table.

Table 1: Comparative Summary of the related works

Reference	Method	Dataset	Result	Limitation
Gutiérrez et al. [7]	Comparison of AutoCAD 2025 vs. AutoCAD Mechanical 2025 using performance metrics and creativity rubrics	Undergraduate mechanical engineering students	AutoCAD Mechanical improved efficiency and creativity	Short-term study, single-discipline focus, no user feedback
Eltaief et al. [8]	CAD Model Automatic Assessment (MAA) Tool using parametric,	Mechanical CAD models in an academic setting	Efficient automation of model evaluation	Limited cross-platform validation, depends on teacher-set parameters

	geometric, and feature-based evaluation			
Zhang et al. [9]	SF6 dial pointer recognition using OpenCV, CAXA, and socket communication	Dial images with angle readings	0.69° average error, high precision	Limited generalizability, depends on specific software
Fakhry et al. [10]	Survey with 59 students and 21 educators comparing CAD vs. hand drafting	Architecture coursework and field visits	CAD preferred for accuracy and efficiency	Risk of overusing copy-paste, lack of site context integration
Hsu et al. [11]	Integration of graphic design software in makeup design teaching via experiments and questionnaires	Cosmetology students and experts	Halved design time, improved instructional effectiveness	Initial learning curve, software-dependent (e.g., mirror function)
Zhang [12]	LSTM and attention-based model for automated brush painting (Python + TensorFlow)	FaceX dataset	98.63% accuracy, 98.75% F1 score	High processing cost, dataset-sensitive
Cheng et al. [13]	Computer vision using wavelet denoising, feature fusion, and style transfer	WikiArt and OilPainting datasets	95%+ style classification, 90% sentiment accuracy	Reduced accuracy on non-benchmark, real-world art

Research fills a critical gap by focusing on the absence of intelligent, automatic assessment systems for AutoCAD-based drawings in educational settings. Research combines image processing and vector transformation techniques to provide accurate, objective, and scalable assessment, whereas existing solutions concentrate on manual review or limited automation. The research helps to modernize CAD education, lessen the workload of instructors, and improve the learning experience for students with limited CAD competency by bringing automated outcomes into line with human grading standards and increasing the efficiency of drawing interpretation.

3 Image processing applied to computer graphics examination-related technologies

The use of MATLAB for graphics processing is because MATLAB has strong matrix operation capabilities, so the processed graphics are represented in the form of matrices or vectors [14-15].

Funded by: Daqing Normal University Youth Fund Research Project (No.: 9ZQ08; Teaching Research Project of Heilongjiang Bayi Agricultural University (Project Title: Research and Application of Paperless Exam System in Computer Graphics Courses. The images produced by the differences are similar) The measure of the degree, the normalization can be well realized by using the histogram, the calculation amount is small, the operation speed is fast, and it is the most used method now in calculate the Equation (1).

$$Sim(G,S) = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{|g_i - s_i|}{Max(g_i, s_i)}\right) \quad (1)$$

Here, G and S are the histograms of the target image and the source image$N$ is the amount of color space models, is the image attribute of the block area of the target image, and is the image attribute of the block area of the source image. $g_i\ s_i$

The histogram-based method was chosen. After all, it is more appropriate for real-time AutoCAD examination systems because it is faster to execute and has less processing complexity while keeping competitive accuracy. The applicability of techniques like SSIM and cosine similarity in time-sensitive evaluation environments was diminished by the reality that they only slightly increased accuracy but arrived with much longer processing times.

4 Image acquisition and processing

The typical AutoCAD computer drawing examination system design mathematical model can be expressed by Equation (2), and the calculation of the optimal computer processing analysis $P = \{u_1, u_2, \cdots, u_k\}$:

$$min\, Z\,(P_\alpha) = \sum_{i=1}^{k=1} d\left(u_{\alpha_i}, u_{\alpha_{i+1}}\right) + d\left(u_{\alpha_1}, u_k\right) \quad (2)$$

In the formula, α_i is used to describe the reorganization of the K computer-processed analysis point order and $d\left(u_{\alpha_i}, u_{\alpha_{i+1}}\right)$ describes the Manhattan distance between two points.

The path optimization model for examining AutoCAD drawing elements during assessment is represented by equation (2). Practically speaking, each point u_i represents a feature or object like a wall, door, or window that was taken from a student's artwork and represented as spatial coordinates or data blocks. The function $d\left(u_{\alpha_i}, u_{\alpha_{i+1}}\right)$computes the distance in meters between consecutive features, a pertinent metric in CAD since objects are frequently aligned to orthogonal grids. The variable α_i indicates a sequence of such features as identified by the system. Finding the most effective structural match between the student's layout and the reference drawing is part of minimizing the sum of these distances.

The formula above quantifies the spatial deviation, for instance, if the student's layout rearranges or misaligns the four rooms that are connected linearly in the correct drawing. That allows the system to assess not only the elements' existence but also their arrangement in a sequence that makes sense geometrically and conceptually. The following is the specific discriminant in Equation (3). $d(i,j,u)$: Inputs parameters function.

$$d(i,j,u) = \begin{cases} [0,0,0], if\ \ i \geq a\ and\ j \geq a\ and\ u \geq a \\ [i,j,u], if\ \ i < a\ and\ j < a\ and\ u < a \\ [i,j,u], if\ \ i > b\ and\ j > b\ and\ u > b \end{cases} \quad (3)$$

The corresponding drawing processing drawing information feature vector χ_i The expression in Equation (4).

$$l_\varepsilon(g) = (1-\rho) l_\varepsilon(g-1) + \gamma f\left(\chi_i(g)\right) \quad (4)$$

f : Represents the adaptive function corresponding to the feature drawing feature vector χ_i of the drawing process. $\gamma\chi_i(g)$: The corresponding drawing processing analysis of the εth dispensation in the actual application process. Equation (5) contains for processing π_p in Drawing ProcessingII.

$$Acu\left(\pi_p\right) = NMI\left(\pi_p, \pi^*\right) \quad (5)$$

π_p and π_q represent the processing of drawing processing. If less information is shared with the drawing processing base drawing, the base drawing is less accurate. Drawings based on image processing techniques that define the thorough analysis in terms of accuracy and diversity typical illustration based on an image processing technique include [16-17] in Equation (6).

$$Eval\left(\pi_p\right) = \lambda Acu\left(\pi_p\right) + (1-\lambda) Div\left(\pi_p\right) \quad (6)$$

$\lambda \in [0,1]$: The exactness and variety of drawings handed out are the degree of importance in the complete analysis criteria. Equation (6) uses the diversity $pro\left(\pi_p\right)$ of the image processing method's basic processing in Equation (7) to get the probability $Div\left(\pi_p\right)$ of choosing every drawing processing basic analyzing technique as the evaluation's basic processing

$$pro\left(\pi_p\right) = \frac{Div(\pi_p)}{\sum_{p=1}^{B} Div(\pi_p)} \quad (7)$$

to restore the drawing's natural color and recognition, the drawing processing network module works to optimize each reconstructed drawing's color and spatial placement [18–19]. The formula defines the drawing processing network module's loss function Lip. The following processing losses are displayed: unmasked regions, masked regions $L_{style}^1 + L_{style}^2$: Style loss, anti-loss L_{total}^{inp} : Total difference loss, andL_{per} : Perceptual loss in Equation (8).

$$L_{total}^{inp} = 2L_{valid} + 12L_{hole} + 0.04L_{per} + 100\left(L_{style}^1 + L_{style}^2\right) + 100L_{adv} + 0.3L_{var} \quad (8)$$

L: Loss function. The weight of each loss term in Manhattan distance (MD) is determined by examining 50 tests. The actual and unmasked processing modes are used, with M representing the irregular binary mask, I_{dam} representing the damaged mode, and I_{inp} representing the outcome mode in Equation (9-10).

$$L_{valid} = \left\| M \times \left(I_{inp} - I_{dam}\right) \right\|_1 \quad (9)$$

$$L_{hole} = \left\| (1-M) \times \left(I_{inp} - I_{dam}\right) \right\|_1 \quad (10)$$

Rotate and restore the identification points against the original image. h Is the connection point of the opening draw, placed in the drawing parallel to the identification graph $0 \leq k \leq h\left(vx'_{2k+1,i}, vy'_{2k+1,i}\right)$ for each identification point the following rotation operation is performed in Equation (11)

$$\begin{cases} dx'_k = vx'_{2k+1,i} - vx_{k,i} \\ dy'_k = vy'_{2k+1,i} - vy_{k,i} \end{cases} \begin{bmatrix} vx'_{2k+1,i} \\ vy'_{2k+1,i} \end{bmatrix} = \begin{bmatrix} vx_{k,i} \\ vy_{k,i} \end{bmatrix} + \begin{bmatrix} cos(-\theta) & -sin(-\theta) \\ sin(-\theta) & cos(-\theta) \end{bmatrix} \times \begin{bmatrix} dx'_k \\ dy'_k \end{bmatrix} \quad (11)$$

For each drawing P_i and $\tilde{P}_i$, calculate its barycentric coordinates after removing the last point. In the formula, h is the length (number of nodes) of the i-th graph after the original graph is split, h'_i is inserted into the length that has been found, and Equation (12–13) computes the next two offset values.

$$\begin{cases} \overline{vx'_i} = \frac{1}{h'_i-1}\sum_{k=1}^{h'_i-1} vx'_k \\ \overline{vy'_i} = \frac{1}{h'_i-1}\sum_{k=1}^{h'_i-1} vy'_k \end{cases} \begin{cases} \overline{vx_i} = \frac{1}{h_i-1}\sum_{k=1}^{h_i-1} vx_k \\ \overline{vy_i} = \frac{1}{h_i-1}\sum_{k=1}^{h_i-1} vy_k \end{cases} \quad (12)$$

$$\begin{cases} \Delta x_i = \frac{1}{2h_i-2}\sum_{k=1}^{h_i-1}(vx_{k+1} - vx_k)p_k \\ \Delta y_i = \frac{1}{2h_i-2}\sum_{k=1}^{h_i-1}(vy_{k+1} - vy_k)p_k \end{cases} \quad (13)$$

Anzhao Equations (13-17) respectively compute the recognition points of the perpendicular and parallel organized of each drawing.

①$\Delta x_i \neq 0 \&\& \Delta y_i \neq 0$

$$\begin{cases} qx_j = \sum_{\{i|\frac{i}{c}=j\}} \frac{\overline{vx'_i} - \overline{vx_i}}{\Delta x_i} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j \circ \alpha \\ qy_j = \sum_{\{i|\frac{i}{c}=j\}} \frac{\overline{vy'_i} - \overline{vy_i}}{\Delta y_i} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j \circ \alpha \end{cases} \quad (14)$$

②$\Delta x_i = 0$, $\Delta y_i \neq 0$

$$\begin{cases} qx_j = \sum_{\{i|\frac{i}{c}=j\}} \sum_{k=1}^{h_i-2} \frac{\overline{vx_{k,i}} - vx_{k,i}}{(vx_{k+1,i} - vx_{k,i})p_k} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j\alpha \\ qy_j = \sum_{\{i|\frac{i}{c}=j\}} \frac{\overline{vy'_i} - \overline{vy_i}}{\Delta y_i} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j\alpha \end{cases} \quad (15)$$

③$\Delta x_i \neq 0, \Delta y_i = 0$

$$\begin{cases} qx_j = \sum_{\{i|\frac{i}{c}=j\}} \frac{\overline{vx'_i} - \overline{vx_i}}{\Delta x_i} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j\alpha \\ qy_j = \sum_{\{i|\frac{i}{c}=j\}} \sum_{k=1}^{h_i-2} \frac{\overline{vy_{k,i}} - vy_{k,i}}{(vy_{k+1,i} - vy_{k,i}) \circ p_k} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j\alpha \end{cases} \quad (16)$$

④$\Delta x_i = 0$,$\Delta y_i = 0$

$$\begin{cases} qx_j = \sum_{\{i|\frac{i}{c}=j\}} \sum_{k=1}^{h_i-2} \frac{\overline{vx_{k,i}} - vx_{k,i}}{(vx_{k+1,i} - vx_{k,i})p_k} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j\alpha \\ qy_j = \sum_{\{i|\frac{i}{c}=j\}} \sum_{k=1}^{h_i-2} \frac{\overline{vy_{k,i}} - vy_{k,i}}{(vy_{k+1,i} - vy_{k,i}) \circ p_k} = \sum_{\{i|\frac{i}{c}=j\}} \tilde{b}_i\alpha = c\tilde{b}_j\alpha \end{cases} \quad (17)$$

Aggregated gradients qx_j, qy_j for group j are defined by equations (14)–(17) based on value changes and spacing$(\Delta x_i, \Delta y_i)$. Weighted by coefficients α and transformation parameter $\tilde{b}_i$, gradients are calculated using either straight finite differences or multistep approximations, depending on whether x/y differences are zero. Calculate numeric information values for each plot in Equation (18).

$$\tilde{m}_j = \begin{cases} 1, \frac{qx_j + qy_j}{2} > 1 \\ 0, \frac{qx_j + qy_j}{2} < 1 \end{cases} \quad (18)$$

Once the digital data has been extracted, verify that the identification is valid. The method recognizes similarities between the unique recognition and the extracted acceptance by using the correlation coefficient $cor(m, \tilde{m})$in Equation (19).

$$cor(m, \tilde{m}) = \frac{\sum_{i=0}^{n-1}(m_i\tilde{m}_i)}{\sqrt{\sum_{i=0}^{n-1} m_i^2}\sqrt{\sum_{i=0}^{n-1} \tilde{m}_i^2}} \quad (19)$$

The digital information $\tilde{m}$ is taken from the recognized graphics, and the correlation coefficient between the digital data m and m is$cor(m, \tilde{m})$.

5 DXF file format

DXF is a data interchange file. AutoCAD supports saving and reading of DXF format files to exchange data with other applications. The DXF file is an ASCII file, so it is helpful to use it as the evaluation basis for the answer, check the correctness and rationality of the software production, and design appropriate scoring rules [20-21]. The proposed AutoCAD test system incorporates image-based similarity scoring with rule-based methods like vector comparisons and DXF parameter matching, ensuring both structural and visual accuracy in assessment, aligning with human evaluation standards, and ensuring a comprehensive evaluation process.

The DXF file consists of six parts: HEADER, CLASSES, TABLES, BLOCKS, ENTITIES, and OBJECTS. Each segment starts with group 0-SECTION and ends with group 0-ENDSEC. The format used here is FORTRAN I3, and the next line of different integer values represents different parameter values, such as strings, integer values, real numbers, etc., which have different meanings.

The DXF parsing method compares graphic primitives based on spatial coordinates from entity definitions. The alignment between student and reference drawings is evaluated using coordinate-based geometric matching. A tolerance criterion accounts for small inconsistencies. Only relevant geometric aspects are highlighted by filtering layer and annotation data.

The system manages multiple DXF layers by parsing each layer separately and comparing those using specific drawing components. DXF entity attributes interpret line styles, allowing for small variations. DXF text entities extract annotations, including text and dimensions, and assess alignment consistency, position, and content about the standard drawing.

Geometric matching of drawing elements and DXF file parsing are the primary methods used for scoring, while image features help confirm the correctness of robotic reproduction.

6 Examination system processing flow

When candidates open the examination questions, they are automatically loaded into the examination system through the interface of VBA and AutoCAD. After the examinee completes the answer, the submit action is executed, and the automatic evaluation engine is started. The software runs in the background, firstly outputs the candidates' answers to the DXF file, detects the corresponding standard answer DXF file according to the test question number, compares, and calculates the score according to the scoring parameter table of the test question package. Then upload it to the server and record it. The design process of the computer drawing test system is displayed in Figure 1.

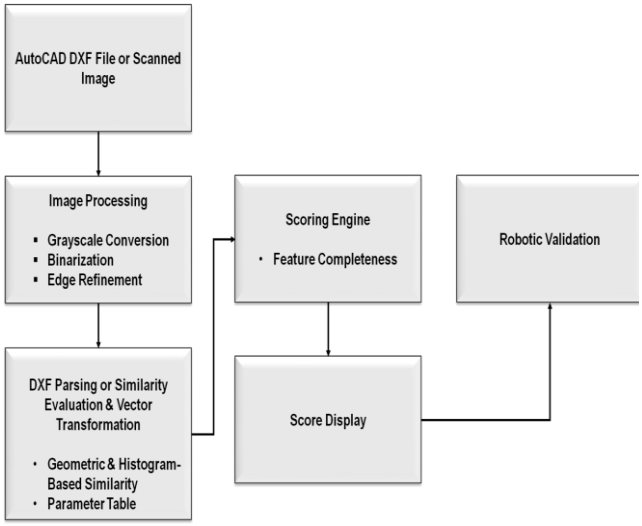

Figure 1: Processing flow of computer graphics examination system.

7 Development tool selection

Because the system is built in AutoCAD, it is executed in AutoCAD, the commonly used software is Visual LISP, VisualC, VisualB a total of three kinds [22], Table 2 is a comparison of the above three kinds of software.

Table 2: Feature comparison of three programming languages.

	flexibility	Easy to learn and use	confidentiality	running speed
Visual C	good	Difference	good	quick
Visual LISP	Difference	good	Difference	slow
Visual B	good	good	good	quick

As can be seen from Table 2, the Visual LISP language is easy to learn but lacks flexibility when completing complex system software. Visual C has strong functions and high flexibility, but it is relatively complex, and programmers have high requirements for computer knowledge, making it difficult to use and grasp quickly. Visual B has the advantages of both Visual LISP and Visual C.

Disadvantage, this is one of the reasons for AutoCAD to switch to Visual B support. Therefore, to develop this system, it is appropriate to use Visual B.

AutoCAD has built-in VBA comprehensive development tools. (VisualBasicforApplication).

8 Design process of computer graphics examination system

Compile the source program with GCC. The driver of the camera is uvcvideo, which supports two formats, YUYV and MPJEG. The device supports the image file imagebmp.bmp captured by the USB camera, such as streaming I/O operations.

Use the ARM-Xilinx-Lnux cross-compilation environment to cross-compile the source files, and copy the executable files generated by compilation to SD. Use the command ARM-Xilinx-Linux-gnuueab-gccv4l2 grab. Compile the c-ozed-camera program, copy the compiled executable file zeed-camera to the Zed-board, connect the USB camera to the Zedboard, connect the cd to the /dev folder, and use the ls command to confirm whether the dev directory is There are videoO devices. Executable files, if

any. Before executing the file, command chmod+x zed-camera or chmod777zed-camera to obtain the executable permission of the file. The former is only valid for the current user; the latter is valid for all users. Execute the executable program according to the command zed-camera, and as shown in Figure 2, code 1 shows the HyperTerminal code.

Code 1: Information is displayed on the HyperTerminal.

Support format:

1. YUV 4: 2: 2($YUYV$)

2. $MJPEG$

$fmt.type$: 1

$pix.pixelformat$: $YUYV$

$pix.height$: 480

$pix.width$: 640

$pix.field$: 1

$init/dev/video0$ [OK]

$grab\ yuyv\ OK$

$save/usr/image\_yuv.yuv\ OK$

$change\ to\ RGB\ OK$

$save/usr/image\_bmp.bmp\ OK$

The USB camera used supports both YUYV and MJPEG. The collected pictures in the two formats are saved in the /usr folder and can be displayed in the picture browser.

A complete digital image processing system requires an image display system in addition to the image collection system. Add a display interface developed by Qt on Linux to display the collected images.

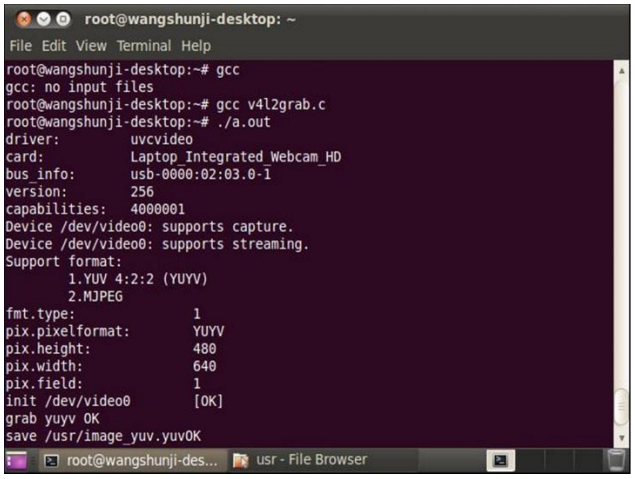

Figure 2: The program obtains the picture successfully.

9 Vector transformation of images

Using a vector drawing computer as input, before drawing, the target image needs to be converted into a vector diagram suitable for the execution of the drawing computer. As shown in Figure 3, the process includes grayscale conversion, binarization, isolated pixel removal, edge refinement [23-24], position restriction, continuous curve detection, synthesis, and other actions.

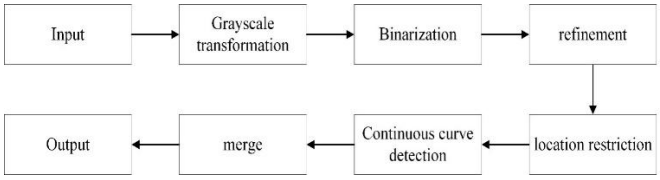

Figure 3: The vector transformation process of the image.

The system uses an image-to-vector procedure to extract vector features from rasterized student outputs for comparison with the standard, ensuring consistent evaluation despite the vector-based nature of AutoCAD drawings, which standardizes various input formats like scanned or non-DXF submissions in Equation (20).

For processing convenience, first, convert the 3-channel color image collected by the camera into a single-channel grayscale image.

$$f = f_R * 0.299 + f_G * 0.587 + f_B * 0.114 \quad (20)$$

Heref_R,f_G,f_B respectively represent a 3-component image in the RGB space, and f represents a transformed grayscale image.

An adaptive threshold technique was used to transform the acquired grayscale image into a binary image [25–26]. Establish the binarization threshold as T ($a \le T \le b$) and ascertain the image's gray value range $[a, b]$ in Equation (21).

$$f_T(x,y) = \begin{cases} 1, f(x,y) \geq T \\ 0, f(x,y) < T \end{cases} \quad (21)$$

The plotter uses it to verify the accuracy of the vector transformation by creating a physical reference by converting standard images to vector paths. The following assures that student drawings are appropriately interpreted by the system's scoring engine, which is based on picture similarity and DXF matching. As a result, both digital and tangible elements support evaluation accuracy and consistency.

Among them, f_T represents the transformed binary image. An example of the transformed effect is shown in Figure 4.

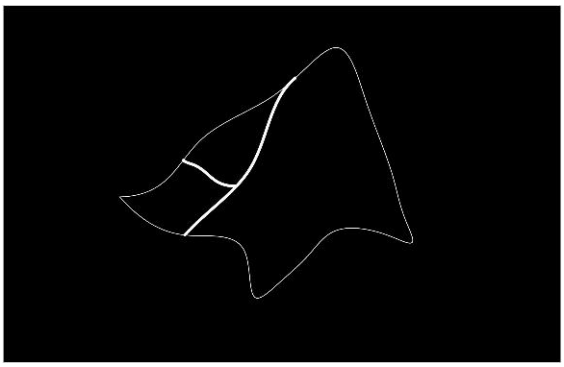

Figure 4: Example of a binarized image.

Through skeleton extraction, the image edge curve with a single pixel width is obtained as shown in Figure 5.

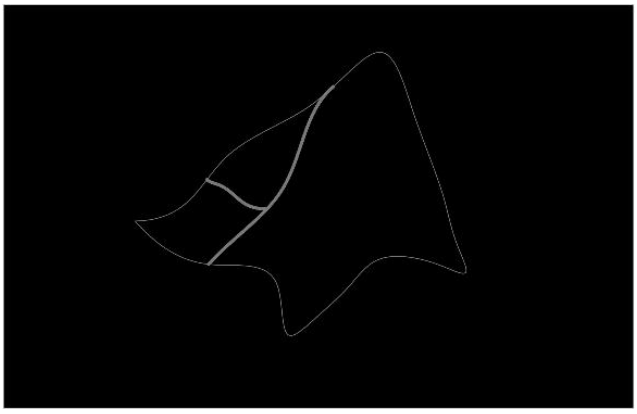

Figure 5: Refinement of the image.

A single-pixel-width edge was consistently formed by the refinement process in Figure 5. For the drawn image to be the center of the canvas, the image must be snapped in position, leaving only the valid portion of the image. The method in this paper first obtains the contour of the effective image through the edge detection algorithm, determines the four outermost pixel points, and then cuts the rectangle determined by the four points to obtain the required image and its coordinate information.

As shown in Figure 6, using different thicknesses to represent different vector curves, the image consists of 4 curves in total.

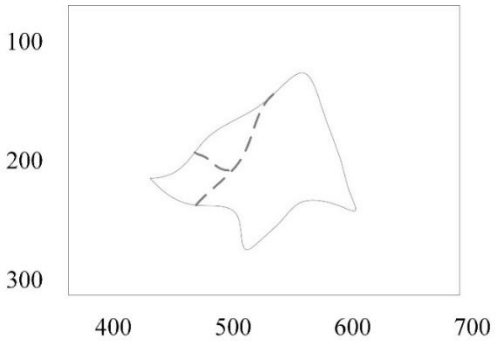

Figure 6: Initial vector curve.

To further advance the drawing effectiveness of the drawing computer and reduce the number of actions of the drawing computer to raise and drop the pen, the divided vector curves are merged, and the adjacent non-closed vector curves are converted into closed curves. As shown in Figure 7, after merging and optimization, the vector curves in the figure are reduced from 4 to 3.

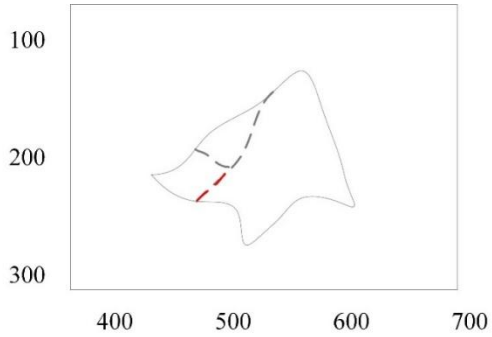

Figure 7: Merged and optimized vector curves.

Vector curves were successfully decreased from 4 to 3 by the merging stage without sacrificing structural integrity in Figure 7 enhancing drawing efficiency. After the above series of image processing operations, the target image to be drawn can be converted into a vector curve recognizable by the drawing computer, and the drawing operation can be performed after being downloaded to the computer actuator.

Therefore, image entropy can be selected as a characterization feature of Chinese paintings, calligraphy images, and man-made images [27-28]. Equation (22) uses the image entropy$p(z_i)(i = 0,1,2,\cdots,L-1)$as a random variable that represents grayscale, where L is the number of identifiable grayscales and the related histogram.

$$e = -\sum_{i=0}^{L-1} p(z_i)\, log_2\, p\,(z_i) \quad (22)$$

From the nature of entropy, the average uncertainty of the equal probability distribution source is the largest, and the uncertainty of the random variable distribution is the largest at this time. The images of Chinese painting and calligraphy are obtained from nature, and artificial images are produced by people's subjective thoughts, so the images of Chinese painting and calligraphy are more complicated than artificial images.

The image's edge, with grayscale variation, boundary, and direction, contains the most image information. Systematic measure measures regional difference, maximal when all levels are equal [29]. The system employs DXF parsing and vector manipulation to address edge scenarios, compensate for scaled or rotated drawings, reduce partial occlusions, and validate components across layers before scoring, thereby preserving grading accuracy and enhancing robustness, while addressing incorrect layer utilization. The appropriate histogram is making$p(z_i)(i = 0,1,2,\cdots,L-1)$, where L is the number of distinct gray levels, and Equation (23) defines the consistency$U$.

$$U = \sum_{i=0}^{L-1} p_2(z_i) \qquad (23)$$

From the perspective of the generation mechanism of Chinese paintings, calligraphy images, and artificial images, Chinese paintings, and calligraphy images have local obvious recognition and other local features [30]. Therefore, consistency can be a feature that distinguishes these two images.

The second-order moment (homogeneous variance$\sigma^2(z) = \mu_2(z)$) is another important feature of the identification feature. It represents the measure of gray-level contrast and can establish a descriptor about smoothness, which is expressed by Equation (24).

$$R = 1 - \frac{1}{1+\sigma^2(z)} \qquad (24)$$

A region's relative brightness smoothness is measured by its cleanliness. $R = 0$: In the area with constant brightness; $R = 1$ in the area where the gray level value deviates significantly.

10 Compile and make runtime library files

In the directory f where the project is located, use the command qmake-Project to obtain the project file lab2 to generate qtcamera.pro. Then use the qmake command to generate the makefile file, and use make to compile the executable file.

The execution of the Qt software depends on the executable library, which is created and mounted to the reference directory. Go to the directory where the installation files were extracted and enter the following command.

The "Compile and Make Runtime Library Files" part supports the image capture component for image-to-vector transformation, creating reference vector diagrams and verifying robotic drawing reproduction. To ensure end-to-end integrity of the suggested evaluation workflow, supporting visual comparison and physical drawing validation, even though not directly related to CAD scoring. Algorithm 1 displays the command to compile the executable file.

Algorithm 1: Library Files to installation and extracted command

$dd\ if = /dev/zero\ of = qt\_lib\_ext4.img\ bs = 1M\ count = 80$

$mkfs.ext4 - F\ qt\_lib\_ext4.img$

$chmodgo + w\ qt\_lib\_ext4.img$

$mount\ qt\_lib\_ext4.img - o\ loop/mnt$

$cp - rf/usr/local/Trolltech/Qt - 4.7.3/*/ mntchmod\ go - w\ qt\_lib\_ext4.$

img

$umount/mnt$

Therefore, the library files under the /usr/local/troltech/Qt-4.7.3/ folder are all included in the newly made 80M image file. The library is ready.

First, the AutoCAD exam questions are classified according to the knowledge points of the exam. The important functions and knowledge points of AutoCAD are drawing and editing of graphics, dimensions and dimensions, text styles and annotations, setting of environment variables, query, view scale, block, pattern filling, etc. [14]. Each exam question sets a scoring parameter table according to the knowledge points.

The image processing technique is a simulation algorithm that mimics the solid annealing process in real life. This process involves heating and cooling a solid, causing disorder and increasing internal energy [16]. The particles are then sorted slowly, reaching equilibrium at every temperature. The image processing method consists of two stages: drawing processing and recognition. The specific steps include achieving the ground state at room temperature, minimizing internal energy, and achieving the equilibrium state at every temperature.

1) Each rendering packet is sent at a specific time interval, and the source node gets ACK or NAK feedback information to create a feedback matrix T that keeps the update up to current. The origin node processes N rendering packets for K receiving nodes.
2) After the resource node has processed N packets, it enters the retransmission phase with time. All missing packets make up the largest coefficient $D = \{X_1, X_2, X_3, \cdots, X_n\}$ in the set $G = \{g_{i1}, g_{i2}, g_{i3}, \cdots, g_{in}\}(1 \le i \le M_{max}())$ coefficient vector M_{max} (chosen randomly from a limited domain) to recommend all missing plotting packets.F_q generates M_{max} recommendation packages. The maximum number of lost packets at all nodes of M_{max} is Equation (25).

$$M \underset{i\in\{1,2,\cdots,K\}}{max}\left\{\sum_{j=1}^{K} T(i,j)\right\}_{max} \quad (25)$$

3)After resending the recommended drawing package, each receiving node approximates and shows the arrangement of its own recommendation vector matrix G. M_{max} If $r_i \neq N$, the node means that G does not reach the complete permutation, then the node needs to notify the source node and resend some recommended packets, and G can be a complete permutation. Here by indicating the required recommendation grouping, the specific situation in Equation (26)

$$N_i = \begin{cases} N - r_i, r_i \le N \\ 0, r_i \ge N \end{cases} \quad (26)$$

in the formula$i = 1,2,\cdots,K$.

In the drawing resend phase, if the receiving node receives the recommended drawing packet, it is 0. When a node loses two recommended packages R_i M_{max} N_i $R_i$then$N_i =$ 2。

4) The source node updates based on the feedback value of each receiving node, and generates the recommended group key algorithm in the new retransmission stage.N_i $M_{\max}$ M_{max}(4)。

5) 3) and 4) are repeated until all receiving node vector matrices are equal to N. That is, M_{max}, with no lost packets, the receiving node can decode the original drawing packets using Gaussian elimination.

It can be seen that the differences between the ERA and AutoCAD computer drafting methods presented here are mainly shown in the following points.

1) Image processing methods have low complexity in combining lost packets. The AutoCAD computer drawing method needs to update the feedback matrix to determine the different types of packets, and the image processing method not only combines all lost packets for retransmission but also the number of recommended packets is determined by Mmax.

2) The image processing method is not affected by the distribution of lost packets, and the number of recommended packets is determined mainly by the receiving node with the most lost packets. Algorithm 2 shows the pseudocode of the main module.

Algorithm 2 Pseudocode of the main module

```
function main():
Input
 image = getImageInput()
dxf = getDXFInput()
 Preprocessing
gray = toGrayscale(image)
   binary = binarize(gray)
   edges = refineEdges(binary)
vector_img = extractVectors(edges)
 DXF Feature Extraction
student_feats = parseDXF(dxf)
ref_feats = loadReference ()
 Scoring
hist_score = histogramSimilarity (vector_img, ref_feats)
dist_score = sum(manhattanDist(student_feats[i], ref_feats[i]) for i in range(len(ref_feats)))
comp_score = completeness (student_feats, ref_feats)
 Final Score
final_score = 0.5 * hist_score + 0.3 * (1 - normalize(dist_score)) + 0.2 * comp_score
print("Score:", final_score)
```

```
Retransmission & Drawing (Optional)

  packets = feedbackRetransmit(preparePackets(vector_img))

  if final_score>= threshold:

drawRobot(pathPlan(packets))
```

11 Examples and results analysis

In the specific operation of Auto CAD computer drawing pictures, by comparing the answer pictures of the two students with the correct answer pictures, this operation can also test the rationality of the computer program system. The graph is divided into three different types of CAD drawings, the graphs of the same size as the standard picture are cut out, a folder is created to save them together, and then the similarity calculation method is used to calculate the corresponding answer. The import system of the A and B pictures given by the two students is shown in Figures 8 and 9 below.

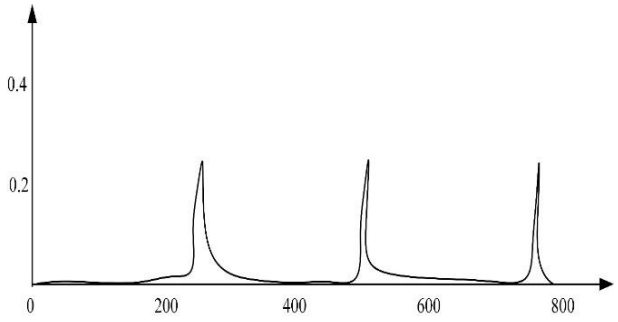

Figure 8: Calculation program for reading A students' scores (92).

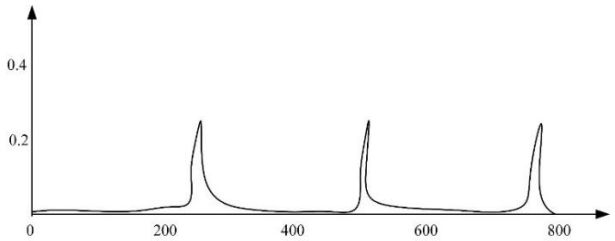

Figure 9: Calculation program for reading B students' scores (80).

Histogram-based comparison methods were used to calculate the similarity scores between the student drawings and the reference. Early instances (Students A and B) are depicted in Figures 8 and 9, which closely match grades assigned by humans.

In the input drawing of student, A, the student has completed the axis, walls, doors and windows, as well as some dimension display, the configuration of stairs and furniture is lacking, and the score of the project test paper is 92. Teachers who graded the papers by hand achieved 92 grades. The input B student diagram completes the display of the axis, doors and windows, part of the wall, and part of the size. The placement of furniture, stairs, and a part of the wall was incomplete, and the score for the program volume was 80. Teachers who manually graded the papers achieved 80 grades. According to the output grades of students A and B, the program calculation results based on the similarity principle are consistent with the integer part of the manually collected results, and the decimal point can be rounded off.

Image similarity and CAD content evaluation are included in the scoring. First, histogram-based similarity is used to compare answer photos to standard images. After that, parsed DXF files are used to evaluate CAD-specific aspects, such as axes, walls, doors, and dimensions. Student A and B's scores (92 and 80) match the hand-assessed results, indicating both visual accuracy and content completeness, which could be explained by the blended technique.

Using the above design scheme, a suspended drawing computer drawing examination system based on a servo motor drive is developed. The main parameters are shown in Table 3.

Table 3: The table of drawing computer parameters

quality(kg)	white board height (m)	Hanging point spacing(m)	Supply voltage(V)	maximum torque(kg/cm)	Rotating speed(rad/min)
0.335	0.86	0.45	11.1	2.22	300

The servo motor-powered drawing machine physically reproduces digital drawings to verify the accuracy of the system's vector interpretation. The machine provides real execution for verifying vector outputs and evaluating picture processing integrity, ensuring the practical robustness of the suggested AutoCAD evaluation system. Vectorizer outputs maintained an average speed of 1.75 cm/s and a drawing accuracy of better than 0.1 cm, according to quantitative validation using the drawing robot (Table 3). That suggests the vector conversion pipeline had little distortion. However, when the result is weak contrast edges or overlapping stroke regions during binarization, the method introduces small alignment errors that could impact snapping accuracy or curve continuity. Usually, post-processing techniques like coordinate anchoring and contour-based cropping help to reduce these inaccuracies. As demonstrated by student score comparisons (e.g., students A and B matched human-evaluated scores), the vectorization accuracy generally closely matches manual grading outputs, indicating that

the vector transformation procedure is both mathematically robust and pedagogically reliable for AutoCAD examination assessment.

To facilitate the drawing computer to adjust the drawing position to adapt to different types of whiteboards, an easy-to-operate GUI user interface is designed, which can easily perform target image input, motor position adjustment, whiteboard parameter setting, drawing start and stop control, etc. To validate the strength of the adopted design and the proposed method, a drawing experiment was carried out using the developed drawing computer drawing examination system. After determining the Base and whiteboard height information, perform moment analysis on each force point on the whiteboard, and the results are shown in Figure 10. Among them, Motor Load represents the moment received. It can be seen that the torque is too large only in the area of y=0, and the other areas meet the requirement that the load torque is less than 30% of the maximum torque.

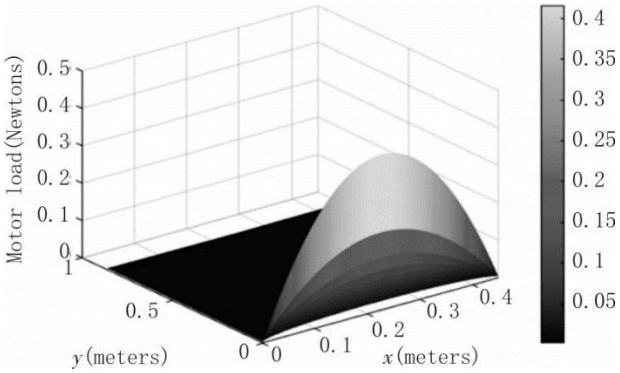

Figure 10: Moment analysis of each point on the whiteboard.

The dead zone positions of the two suspension points are removed, and the positions are limited according to the principle that the load moment is less than 30% of the maximum moment, and the results shown in Figure 11 are obtained.

It can be seen that the motion position does not include the upper left and upper right fan-shaped areas, this is because the two hanging points are positions that the drawing computer cannot reach. In addition, to prevent the motor torque from being too large, the moving area of the drawing computer is limited (the rectangular box area in Figure. 11). To verify the drawing speed and accuracy of the drawing computer, the moving distances of 20 cm, 10 cm, and 5 cm were set respectively, and the average value was obtained after 10 experiments in each group. The outcomes are illustrated in Table 4.

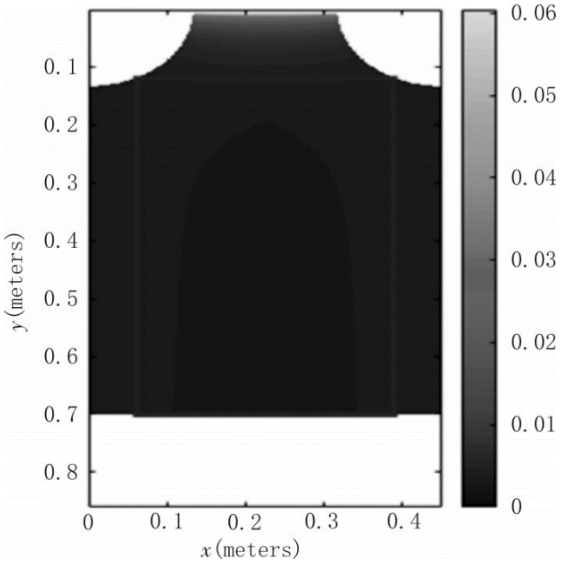

Figure 11: Limiting the movement position of the drawing computer.

Table 4: The experimental results of the drawing speed and accuracy test of the drawing computer.

set distance(cm)	Measured distance(cm)	required time(s)	actual speed(cm/s)	(cm)
20	19.9	11.38	1.749	0.1
10	9.9	5.71	1.733	0.1
5	5.0	2.81	1.780	0.0

From the results in Table 3, it can be seen that the average drawing speed of the computer is 1.75 cm/s, the drawing accuracy is better than 0.1 cm, and the drawing speed and accuracy meet the design requirements. To verify the drawing effect of the drawing computer, several pictures were randomly selected for drawing, and the drawing results are demonstrated in Figure 12.

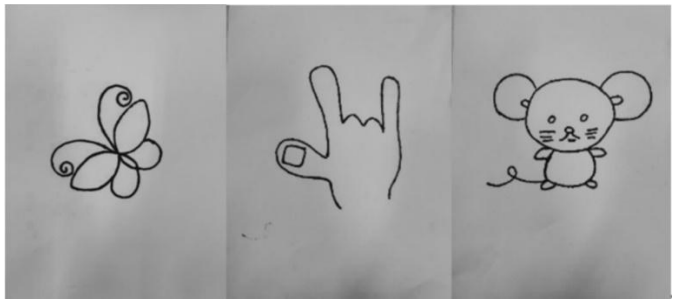

Figure 12: Image rendering example

The proposed AutoCAD assessment system integrates CAD-specific content analysis with histogram-based image similarity for objective, consistent scoring. AutoCAD uses a servo motor-driven drawing machine for physical verification, ensuring higher accuracy, less subjectivity, and practical dependability. The system

surpasses conventional approaches in automation, accuracy, and adaptability for CAD-based examination and assessment activities.

12 Conclusions

For the calculation criteria of the similarity of the pictures, using MATLAB to calculate the picture, the system of drawing the similarity of the pictures, using the students to draw pictures and compare the correct answers, using three different types of pictures and the money-making answers to compare and calculate, calculate and export the correct answer. Realize the function of only scoring by computer. It improves work efficiency and saves manpower and material resources for manual scoring. The development and application market of computer-only scoring systems is ideal. However, a small sample size is a disadvantage. To ensure statistical robustness and show the generalizability of the system's evaluation accuracy, future research will incorporate a broader display of similarity scores across a varied collection of student submissions. Method also features a graphical user interface for user convenience. Complex overlapping designs and problems with contrast could pose problems for the system. Future research could include AI for adaptive scoring refinement, assist 3D CAD review, and improve edge recognition. To demonstrate the method's statistical robustness and generalizability, future research will need to conduct additional examination using a more extensive and varied dataset. A major focus of future research will be thorough statistical validation using larger datasets. The system's analytical depth and evaluation precision will be improved in subsequent work by incorporating quantitative tracking mechanisms during the vector transformation process. The result will allow the calculation of vectorization errors and the identification count of geometric shapes. Large-scale quantitative validation will be incorporated into future research. Future research will take into account more extensive statistical comparisons for a thorough assessment. To enhance item detection and analysis accuracy, future studies will use CNNs trained on annotated CAD datasets to improve drawing structure recognition.

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Optimization of Dynamic Energy Management Strategy for New Energy Vehicles Based on Multi-Agent Reinforcement Learning

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Keywords: battery degradation, energy management strategies, fuel economy, new energy vehicle (NEV), power distribution, scalable satin bowerbird optimizer-driven multi-agent deep Q-Network (SSB-MADQN)

Received: April 14, 2025

The development of New Energy Vehicles (NEVs), such as battery electric vehicles, is vital to addressing global issues like environmental pollution and fossil fuel depletion. However, optimizing their energy management strategies (EMSs) is complex due to conflicting goals, dynamic driving conditions, and system nonlinearity. This study proposes a dynamic EMS based on Multi-Agent Reinforcement Learning (MARL) using a Scalable Satin Bowerbird Optimizer-driven Multi-Agent Deep Q-Network (SSB-MADQN). The approach aims to enhance fuel economy, maintain battery State of Charge (SOC), and reduce battery degradation in real-time driving scenarios. Prior to training, data preprocessing—including min-max normalization and Principal Component Analysis (PCA)—improves learning efficiency. The MADQN framework consists of agents representing subsystems such as the engine, battery, and regenerative braking, each trained using a deep Q-network with three hidden layers (128-64-32 neurons). The dataset comprises 5,000 samples with 13 features, including vehicle speed, power demand, and battery performance. Evaluated on HWFET and WLTC driving cycles, the proposed strategy reduces fuel consumption by 0.912 L (WLTC) and 0.681 L (HWFET) compared to traditional methods. It effectively regulates SOC and reduces high-power discharge events, confirming the robustness of MARL for adaptive and efficient EMS in NEVs.

Povzetek: Raziskava predlaga dinamično strategijo upravljanja z energijo (EMS) za NEV na osnovi MARL (SSB-MADQN). Optimizira porabo goriva, stanje napolnjenosti baterije (SOC) in zmanjšuje degradacijo, s čimer izboljša učinkovitost v realnem času.

1 Introduction

The growing demand for NEVs, which includes hybrids and battery electric vehicles, occurs because they serve as an environmentally friendly replacement for traditional internal combustion engine vehicles that offer improved air quality decreased greenhouse gas emissions, and reliable energy systems [1]. Strong worldwide climate change understanding, along with decreasing fossil fuel reserves, has made NEV development essential for countries implementing sustainable transportation solutions [2]. Conventional EMS approaches, such as rule-based, fuzzy logic, or model predictive control methods, rely on pre-defined heuristics or offline optimization and often fail to adapt in real-time to complex, dynamic environments like varying road gradients, traffic conditions, and driving behaviours [3]. The growing complexity of NEVs and their need for adaptive, real-time decision-making have thus pushed the investigation toward leveraging artificial intelligence (AI) techniques such as machine learning (ML) and reinforcement learning (RL) [4]. Figure 1 shows the dynamic energy management strategy for NEVs.

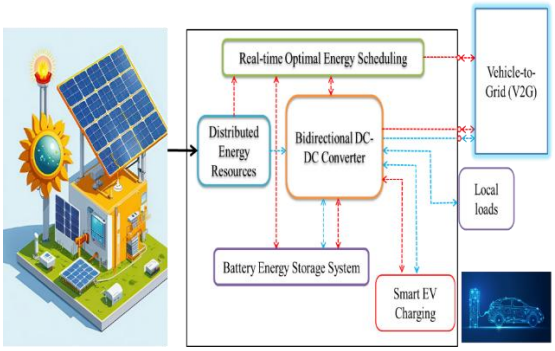

Figure 1: Dynamic energy management strategy for NEVs

Reinforcement learning has shown significant promise in EMS optimization by enabling systems to accumulate reward functions, such as fuel efficiency or battery health [5]. However, most existing RL-based EMS frameworks

operate under a single-agent paradigm, where the entire decision-making process is centralized, which limits scalability and does not fully represent the distributed nature of NEV components. In reality, energy management involves coordination between multiple subsystems [6].

The vehicle dynamics are modeled to include real-world constraints such as regenerative braking, load variations, and battery degradation metrics [7]. Despite various conventional EMS strategies yielding acceptable performance under ideal conditions, they often fail in unpredictable or highly dynamic driving environments. By leveraging the strengths of multi-agent systems and metaheuristic-optimized DL models, it offers a robust, adaptive, and intelligent EMS that is both scalable and energy-efficient. It highlights the transformative potential of AI-driven strategies in the automotive domain, particularly for real-time optimization and sustainable energy utilization in NEVs.

To address these limitations, MARL has emerged as an innovative solution for optimizing EMS in a decentralized and cooperative manner. In MARL-based EMS, different vehicle components are modeled as intelligent agents, such as a battery agent and an engine agent that learn to make decisions based on local observations and collaborate to achieve a global objective. It allows for distributed control, reduced computational complexity, and more effective adaptation to real-time driving dynamics. A novel MARL-based EMS framework is proposed using an SSB-MADQN. The SSB is a nature-inspired metaheuristic algorithm based on the mating behavior of satin bowerbirds, known for balancing exploration and exploitation efficiently. The aim is to enhance fuel economy, sustain battery SOC, and decrease battery degradation under dynamic driving conditions.

1.1 Key contribution

Data Collection: The dataset captures real driving conditions, fuel consumption, power distribution, and battery health metrics specific to NEV scenarios.

Data preprocessing: Applied data cleaning and min-max normalization to standardize input variables, ensuring consistent scale and reducing data noise for learning stability.

Feature extraction: Used PCA to extract 12 principal components, preserving 95% variance for improved training efficiency and dimensionality reduction.

Proposed method: SSB-MADQN, a MARL-based framework with decentralized agents and a Satin Bowerbird-optimized DQN for dynamic NEV energy management.

1.2 Motivation

The motivation for this research is driven by the need for more effective and adaptive energy management strategies for new energy vehicles (NEVs). Current systems face challenges in optimizing fuel efficiency, battery health, and driving performance simultaneously, especially under dynamic driving conditions. By leveraging Multi-Agent Reinforcement Learning (MARL) and the novel SSB-MADQN approach, this research aims to reduce fuel consumption while maintaining optimal battery SOC and minimizing degradation, ultimately contributing to more sustainable and efficient NEV operation in real-world scenarios.

The research is comprised of the following sections: In Section 2, a list of relevant works was presented. In Section 3, the methodology is described. In Section 4, the findings are presented. The discussion portion is provided in Section 5, and Section 6 contains the conclusion.

2 Related work

A novel multiple-input and multiple-output (MIMO) control technique based on Multi-Agent Deep Reinforcement Learning (MDARL) was examined in [8] for the multi-mode photovoltaic EV. Two learning agents would collaborate under the MDARL, utilizing the deep deterministic policy gradient (DDPG) algorithm by implementing a handshaking technique that provided a relevance ratio. To improve fuel economy, [9] provided a unique EV EMS based on the MDARL architecture. Under power limits, the EMS effectively achieved optimal power transmission between the engine and battery.

The optimal functioning of a fleet of EVs that were directed to supply power to a group of clients at various places was covered in [10]. MARL was used in a Decentralised Markov Decision Procedure reformulation framework to be practicable for a fleet of EVs to function well and provide energy to numerous clients at various places. A unique optimum energy management approach based on the suggested MDARL technique was presented in [11]. It used a deep neural network to train a strategy based on multi-agent deep deterministic policy gradient (MADDPG) learning capacity and stacked denoising auto-encoders. By considering the different characteristics of both electrical and thermal energies.

A MADRL optimization approach was proposed in [12] for energy control with EV charging development. To determine the optimal choice, the aggregator and prosumers were designed to be intelligent agents that communicate with one another. Utilizing EV battery scheduling, prosumers might save on power costs. A new Multi-Agent ActorCritic (MA2C) system was examined in [13], which was specifically designed for mixed-traffic situations. The MA2C algorithm offers an extensive method of managing urban traffic that prioritizes effectiveness, safety, and passenger security.

To effectively recommend public charging stations, [14] anticipated a Multi-Agent Spatio-Temporal Reinforcement Learning (Master) that takes into consideration several

long-term spatiotemporal characteristics. The Demand Response potential in smart homes using a multi-agent reinforcement learning framework enhanced with BiLSTM and Attention Mechanism for improved data efficiency and handling stochastic household loads [15]. The BiLSTMA-MADDPG model improves data efficiency, convergence speed, and scalability in controlling household appliances under limited training samples. Table 1 presents recent advancements in multi-agent reinforcement learning (MARL) for energy management in smart systems. It highlights diverse applications ranging from EVs and smart grids to smart homes using algorithms like MADDPG, MA2C, and BiLSTMA-MADDPG. While most approaches show improved performance in energy savings and efficiency, common limitations include coordination complexity, high computational needs, and data inefficiency.

Table 1: Contrast examination of traditional works

Ref.	Year	Area Focused	Algorithms	Limitations	Performance
[8]	2023	Energy Management in Multi-mode plug-in hybrid EVs	MADRL, DDPG, Hand-shaking Strategy, Relevance Ratio	Requires careful tuning of DDPG parameters; learning performance is sensitive to learning rate	Energy savings can range from 4% to 23.54% when compared to a single-agent system and a rule-based system.
[9]	2025	Hybrid EVs, Energy Management Strategy	MADRL, MADDPG	Complexity in multi-agent coordination, simulation-based validation only	Fuel consumption was reduced by 26.91% (WLTC) and 8.41% (HWFET), improving EMS robustness.
[10]	2022	Smart Grids, Multi-Agent Systems, EVs.	MARL, Decentralized Markov Decision Process (Dec-MDP), Actor-Critic Networks	High initial training complexity assumes accurate agent-environment modeling.	Significant reduction in simulation time; superior scalability and efficiency
[11]	2023	Optimal Energy Management, Smart Grid, Multi-Energy MicroGrids.	MADRL, Stacked Denoising Auto-Encoders framework	Requires high computational resources, complexity in decentralized implementation, and training convergence	Achieved optimal dispatch of electric and thermal energies, and reduced emissions and costs.
[12]	2023	Smart Grid Energy Management, EV Scheduling, Solar Photovoltaic (PV) Integration	MADRL, Real-Time Pricing, Smart Agent Interaction	High computational requirements for real-time DRL.	Mean power consumption was reduced by 9.04% (vs. no EV usage) and reduced by 39.57% (vs. conventional pricing)
[13]	2024	Smart Cities, Autonomous Vehicles, Sustainable Mobility	MA2C, Reinforcement Learning, Actor-Critic Architecture	Complexity of multi-agent coordination; Requires realistic traffic data for deployment	Outperforms existing models in lane-changing efficiency, safety, comfort, and inter-vehicle cooperation.
[14]	2021	EVs Charging Recommendation, Smart Mobility, DRL	MA2C Framework, Centralized Attentive Critic, Delayed Access Strategy	Required coordination among distributed agents	Outperforms 9 baseline approaches in recommending charging stations.
[15]	2023	Demand Response in Smart Homes	BiLSTMA-MADDPG (Multi-Agent RL)	Non-stationary environment; data inefficiency	Improved data efficiency, faster convergence, and better scalability with small samples.

3 Methodology

The methodology involves modeling the NEV's energy system as a multi-agent environment with engine and battery agents. Real-time driving data undergoes data cleaning and min-max normalization, and PCA for feature extraction. AnSSB-MADQN is employed to optimize power distribution. Trained on WLTC and HWFET cycles, this strategy improves fuel efficiency, stabilizes SOC, and reduces battery degradation, enabling adaptive, real-time energy management under dynamic driving conditions. Figure 2 presents the proposed methodology's overview.

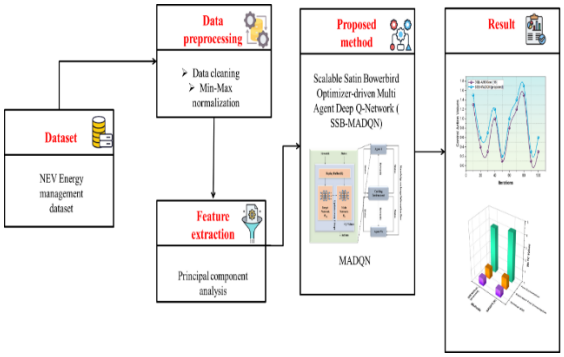

Figure 2: Proposed methodology overflow

3.1 Data collection

The NEV energy management dataset was collected from the Kaggle source. It is meant to assist in finding the most effective ways to save energy in NEVs, using the approach of MARL. It
includes data about real-world traffic, energy distribution, mileage, and battery health for multiple driving routines. 70% of the dataset was used for training and 30% for testing to evaluate performance under diverse scenarios.
Source:https://www.kaggle.com/datasets/ziya07/nev-energy-management-dataset/data

3.1.1 Data Description

The NEV Energy Management Dataset features 5,000 records with 13 attributes for measuring vehicle speed along with acceleration, power demand, fuel usage, and battery performance across different driving conditions. The system combines essential variables such as engine power, battery power and SOC, battery degradation, and regenerative braking power to assess energy efficiency and sustainability levels.

3.1.2 Data Exploration

The pair plot demonstrates the relationship dynamics between speed, power demand, battery power, SOC, and fuel consumption variables for designing a dynamic energy management strategy in NEVs. The diagonal presentation displays distribution patterns to identify normal or skewed data shapes. The correlations and strong positive associations between power demand and battery power become visible through off-diagonal scatter plots. Figure 3 shows the data exploration.

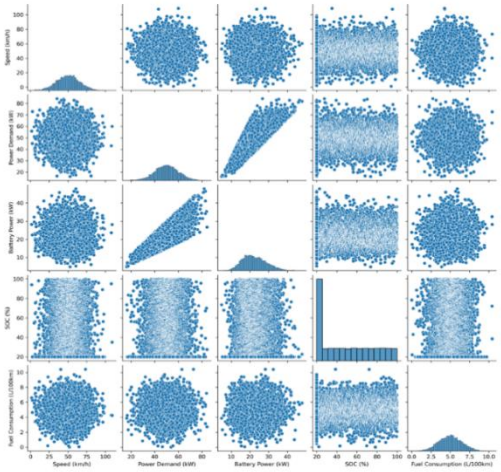

Figure 3: Data exploration outcomes

3.2 Data preprocessing using data cleaning

To clean the NEV energy management dataset, missing values should be handled through mean or median imputation techniques while maintaining sparse data rows. Convert data types to ensure consistency across numerical and categorical fields. The data types should be converted to achieve numerical and categorical field consistency. Reduction of redundant data will occur by eliminating duplicate records. The system needs to identify and handle unusual cases found in energy consumption alongside battery degradation trends. A final test must verify the data balance between driving cycles and efficiency classes.

3.2.1 Min-Max normalization

The process of min-max normalization transforms new energy vehicle energy management datasets into standardized ranges, which improves both model performance and speed of convergence, and accuracy during energy efficiency optimization. Using linear modifications of the original data, min-max normalization creates a balanced set of value comparisons between the data before and after the execution, as follows in Equation (1).

$$W_{new} = \frac{W - \min(W)}{\max(W) - \min(W)} \ldots. \quad (1)$$

W_{new}- The adjusted value derived from the normalized outcomes
W- Old Value
$\max(W)$-The dataset's maximum value
$\min(W)$- The dataset's minimum value

3.3 Feature extraction using PCA

The dynamic energy management technique becomes more efficient by eliminating unnecessary variables and focusing exclusively on critical factors. This results in faster convergence and more accurate decision-making via the MARL framework for energy distribution. PCA was used to minimize the dimensionality of the dataset while retaining the majority of its informational richness. In addition, 5 derived characteristics were designed to capture complicated energy dynamics such as power fluctuation, energy trends, and driving cycle behavior, which are crucial for intelligent EMS control.

By eliminating the class label, each observation in a data set of l observations is mathematically m-dimensional. Assuming that $w_1, w_2, \ldots\ldots, w_l \in \Re^m$. The subsequent procedures for calculating PCA.

Determine the mean vector μ in m-dimensions by Equation (2).

$$\mu = \frac{1}{l}\sum_{j=1}^{l} w_j \tag{2}$$

Determine the observed data's estimated matrix of covariance T by Equation (3).

$$T = \frac{1}{l}\sum_{j=1}^{l}(w_j - \mu)(w_j - \mu)^s \tag{3}$$

Determine the associated eigenvectors and eigenvalues of T, whereby $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_l \geq 0$. Determine the l primary components from the l original variables by Equation (4).

$$\begin{aligned} z_1 &= b_{11}w_1 + b_{12}w_2 + \cdots + b_{1l}w_l \\ z_2 &= b_{21}w_1 + b_{22}w_2 + \cdots + b_{2l}w_l \\ &\cdots \\ z_l &= b_{l1}w_1 + b_{l2}w_2 + \cdots + b_{ll}w_l \end{aligned} \tag{4}$$

It is orthogonal that z_l are uncorrelated. As much of the initial variation in the data set can be explained by z_1, as much of the residual variance can be explained by z_2, etc. In the most useful data sets, a small number of bigger eigenvalues often outnumber the others, as follows in Equation (4). Where the proportion maintained in the data format is denoted by z_l.

$$\gamma_l = \frac{\lambda_1+\lambda_2+\cdots+\lambda_n}{\lambda_1+\lambda_2+\cdots+\lambda_n+\cdots+\lambda_l} \geq 80\% \tag{5}$$

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the input space. Although the original dataset consisted of 13 attributes, only 12 numeric features were used for PCA, excluding the non-numeric target column. PCA transformed this 12-dimensional feature space into 6 uncorrelated principal components, capturing over 95% of the total variance and improving model training efficiency by eliminating redundancy. After applying min-max normalization, PCA reduced the feature space to 6 principal components, maintaining more than 95% of the total variance while minimizing duplication, boosting the energy management model's learning efficiency. Figure 4 shows the PCA-based feature contribution to the first principal component, which explains the most variation. This information assists in determining the most significant elements for EMS optimization. Notably, this representation is based on the PCA loading matrix before dimensionality reduction. Figure 4 shows PCA-Based Feature Importance Output for Energy Management Optimization.

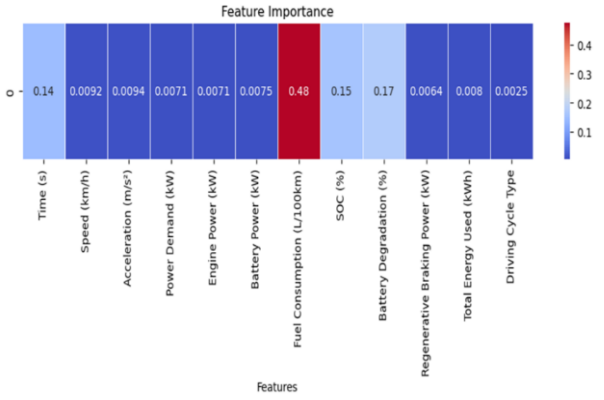

Figure 4: PCA-based feature importance output for energy management optimization

- **Data Cleaning (13 features):** Outliers, impossible values (e.g., negative fuel), and missing values were handled through imputation and filtering.
- **Normalization (13 features):** Each feature was scaled to a standard range (mean = 0, std = 1) for consistent learning performance.
- **PCA Application:** Principal component analysis reduced the final 18-dimensional space to 6 principal components, capturing >95% variance, enhancing model training speed and generalization.

While the original dataset contained 13 attributes, 5 additional derived features were introduced through feature engineering to enhance the model's ability to capture dynamic driving patterns and battery behavior. For instance, ΔSOC (change in State of Charge) reflects short-term battery discharge rates, offering temporal insights that static SOC cannot. Similarly, features like speed trend and regenerative efficiency were designed to capture vehicle acceleration patterns and energy recovery rates, respectively. These engineered features provide higher-level abstractions that improve the learning model's contextual awareness. PCA was then applied to this 18-dimensional space to reduce redundancy, improve

generalization, and retain the most informative patterns by selecting 6 principal components that preserved over 95% of the variance.

3.4 SSB-MADQN

The SSB-MADQN is a novel framework for dynamic energy management in NEVs. It integrates the SBO to enhance agent policy optimization and exploration within a MADQN environment. By enabling decentralized cooperation among energy management agents, SSB-MADQN effectively balances power delivery among both the engine and battery, optimizes fuel consumption, and mitigates battery degradation under diverse driving cycles. The scalable design ensures adaptability across vehicle platforms, while the optimizer enhances learning efficiency, making SSB-MADQN a robust solution for real-time, intelligent NEV energy management.

3.4.1 MADQN

The MADQN enables dynamic energy management in NEVs by allowing multiple agents (engine, battery, motor) to learn cooperative strategies. Through DRL, each agent optimizes energy distribution, improving efficiency, reducing fuel consumption, and adapting to varying driving conditions in real time. It uses a model-free reinforcement learning strategy, which eliminates the need to explicitly understand the environment's dynamics. Agent 1 observes state t_s and chooses the optimal action at time s to move to state t_{s+1} in traditional Q-learning, based on a value model-free approach. The agent then changes the Q-value after receiving an instant benefit $r(t_s, b, t_{s+1})$at time $s+1$, as shown in Equation (6).

$$Q_{s+1}(t_s, b_s) \leftarrow (1-\alpha)Q_s(t_s, b_s) + \alpha[r(t_s, b_s, t_{s+1}) + \gamma \max_b Q_s(t_{s+1}, b)] \quad (6)$$

In reinforcement learning, γ is a discount factor, $\gamma\, max_b' R_s(t', b')$ is the discounted reward, and $\alpha \in [0,1]$ is the learning rate. The Q-values for every potential state and action for agent 1 are stored in a two-dimensional look-up column with dimensions $\mathcal{T} \times \mathcal{B}$. Consequently, the number of actions and states in a complex system causes the Q-table's size to grow exponentially. Figure 5 presents the MADQN architecture. Every edge server is regarded as an agent in EV. Figure 5 depicts the MADQN framework utilized in the caching environment, with architectural details. The neural networks (Main and Target) are implemented as multilayer perceptrons, with an input layer matching the state dimension (e.g., 50 features), two hidden layers of 128 and 64 neurons, respectively, employing ReLU activation, and an output layer representing the number of potential actions (e.g., two for binary caching decisions). These features are critical to understanding the model's structure and ensuring repeatability.

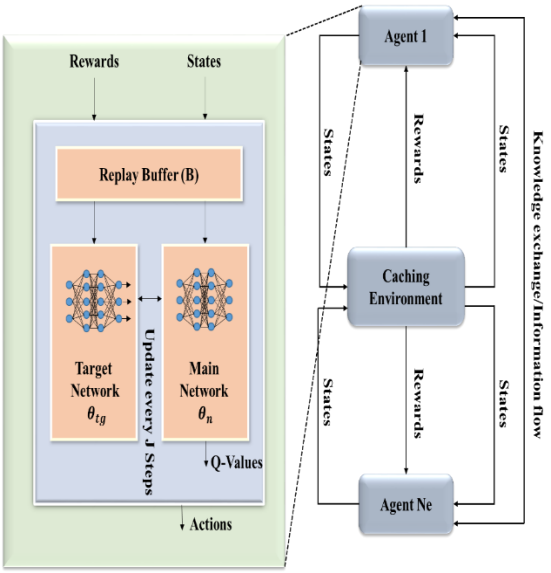

Figure 5: MADQN architecture

In multi-agent reinforcement learning, the replay buffer holds all agents' experiences, which frequently include shared observations, actions, and rewards to capture inter-agent relationships. Each agent's training is stabilized by the target network, which provides constant Q-value targets and is updated on a regular or soft basis. Q-value updates are changed by taking into account not just an agent's action and reward, but also the effect of other agents' activities, employing centralized training and decentralized execution. This allows agents to develop coordinated methods while functioning independently during deployment.

A replay buffer is used to retain the agent's experiences, a target network (θ_{tg}) replicates the main network to offer a steady target for learning, and a main network parameterized by (θ_n) is used to estimate Q-values in the multi-agent environment. First, agent 1 observes the energy demand signal and its states at the time s communicates with neighboring agents (states (t_s) and policies), and selects an action (b_s). For example, suppose that Agent 1 is unable to fulfill the energy storage request. Suppose that three collaborative NEV modules (engine, battery, motor) $(\{i, r\} \in \varepsilon_{nb})$ with a strategy for new energy $q_{F,ji}$and $q_{F,iq}$, where $q_{F,ji} < q_{F,iq}$, have the matching content. This situation results in the selection of the neighboring agent with energy cost, as shown in Equation (7).

$$b_s = \begin{cases} \arg\max_{b\in\mathcal{B}} Q(t_s, b) & o = 1-\epsilon_1-\epsilon_2 \\ random\ b \in \mathcal{B} & o = \epsilon_1 \\ Other\ replacement\ policy\ b \in \mathcal{B} & o = \epsilon_2 \end{cases} \quad (7)$$

Furthermore, it has ϵ_1 and ϵ_2 set to decrease with time. Consequently, the model will eventually choose the best

course of action. It is suggested to explore if the agent does not function well. A collection of recent rewards (R_G) is tracked, and $\in_y$ ($where \ \in_y \ \{1,2\}$)is updated, as shown in Equation (8). The step sizes for modifying the probability $\in_y$ are δ^+ and δ^-, and rth is a reward threshold.

$$\in_y = \begin{cases} \in_y + \delta^+, & \mathbb{E}(Q_G) < r_{th} \\ \in_y - \delta^-, & \mathbb{E}(Q_G) \geq r_{th} \end{cases} \quad (8)$$

The agent moves on to the next state $(t_s + 1)$ for the selected action (b_s), preserves moving in the replay buffer of size, and receives an instant benefit $(r_s + 1)$. During the training stage, agent 1 uses mini-batch descent to train the primary network after selecting a mini-batch of size A from the replay buffer. In every I step, the target network replicates the primary network to provide learning stability, as follows in Equation (9).

$$Q_{s+1} = (t_s, b_t) \leftarrow (1-\alpha) Q_s(t_s, b_t; \theta_n) + \alpha\left[r(t_s, b_t, T_{s+1}) + \gamma \max_b Q_s(t_{s+1}, b; \theta_{sh}) - Q_s(t_s, b_t; \theta_n)\right] + \sum_{i \epsilon M_f} w_{ji} Q_{s-1}(t_s, b_t; \theta_n) \quad (9)$$

Where ω_{ji} is modeled as inversely proportional to the EMS(rF, yx) among $i$and j, and is used to highlight the effect of neighbor I on agent 1.

3.4.2 SSB

The traditional Satin Bowerbird (SB) optimizer struggles to effectively manage the complex, dynamic, and multi-objective nature of energy management strategies in new energy vehicles (NEVs). It lacks the scalability and the ability to deal with several competing priorities, including fuel consumption, battery capacity, and reducing battery degradation. The basic SB algorithm lacks mechanisms for efficiently navigating high-dimensional search spaces or adapting to rapidly changing driving conditions. It also falls short in maintaining solution diversity and handling trade-offs among multiple objectives, often leading to premature convergence or local optima. Furthermore, its limited ability to handle real-time updates and high-dimensional decision spaces reduces its effectiveness in dynamic driving conditions, prompting the need for improved approaches like the Scalable SB (SSB) optimizer. SSB efficiently balances energy distribution between battery and engine systems, adjusts to various driving schedules, speeds up how policies are learned and helps achieve better fuel efficiency, fewer emissions, and longer life of the vehicle battery in complex driving situations.

- ***Logistic Chaos's initialization:***

Although the algorithm's initial population utilizes a random initialization mode according to natural law, a better initialization approach would greatly accelerate the intelligent optimization algorithm's convergence speed. The population is also initialized by the SB using random values. A logistic chaos map was created to improve the starting population's diversity, which in turn led to a better-starting population, which improved the algorithm's accuracy and speed of convergence. Equation (10) illustrates the logistic chaos map calculating method.

$$W_{j+1} = \mu W_j * (1 - W_j) \quad (10)$$

The control parameters μ have a value range of $0 \ to \ 4$. There will be more confusion when the number of μ is higher. The chaotic initialization effect will be amplifiedμ. Equation (11) is used as the population initialization.

$$pop(j).Position = Y(j,:).*(VarMax - VarMin) + VarMin \quad (11)$$

- ***The cauchy variation method:***

Instead of using the conventional SB mutation technique, which produces a shorter peak dispersed at the origin and a longer spread in the remainder, the Cauchy mutation strategy guarantees more disruption near the current population. Equation (12) shows the Cauchy variation approach.

$$W_{j,i}^{s+1} = W_{best} + Cauchy(0,1) \oplus W_{best}(s) \quad (12)$$

Where $W_{best}(s)$ is the location of an individual that requires variation, and $Cauchy$ $(0,1)$ is the typical Cauchy distribution. Equation (13) computes the relevant variation probability.

$$O_t = -\exp\left(1 - \frac{it}{MaxIt}\right)^{20} + o \quad (13)$$

Both the current is represented by $MaxIt$, where o is set at 0.05. The procedure of the Cauchy mutation will not be carried out if q and $< Ps$. Table 2 shows the hyperparameters of SSB.

SSB's chaotic initialization improves exploration by ensuring diverse initial solutions, avoiding local optima, and speeding up convergence. The Cauchy variation, with its heavy-tailed distribution, enables larger step sizes, improving the algorithm's capacity to escape local minima and strike a better balance between exploration and exploitation. These traits exceed typical heuristics, allowing for faster and more efficient optimization.

Table 2: Hyperparameters of SSB

No.	Hyperparameter	Symbol / Name	Typical Value / Range	Description
1	Population size	P	5 – 50	Number of candidate solutions (bowerbirds)
2	Maximum iterations	MaxIter	10 – 100	Maximum SBO optimization cycles
3	Attraction coefficient	α	0.05 – 0.3	Strength of movement toward better solutions
4	Random scaling factor	rand ()	[0, 1]	Random noise for solution diversification
5	Learning rate search range	LR_range	[0.0001, 0.01]	Search space for learning rate
6	Epsilon search range	ε_range	[0.1, 1.0]	Exploration rate range
7	Discount factor search range	γ_range	[0.8, 0.99]	Reward discount factor range
8	Fitness function	F(x)	Avg episodic reward	Evaluate solution quality
9	Movement formula	x_new = x + α * rand () * (x_best - x)	—	Bowerbird movement update
10	Dimensionality of solution	D	3	Parameters optimized (LR, ε, γ)

4 Results and discussion

The result comparison parameters, such as EMS optimization results for different strategies under WLTC, EMS optimization results for different strategies under HWFET, and control action, are used to demonstrate the comparison of the proposed model, SSB-MADQN, for energy management strategy for new energy with the existing techniques, such as MADDPG [9] and Deep Q-learning Adaptive Moment Estimation (DQL-AMSGrad) [16]. The experimental setup is presented in Table 3.

Table 3: Experimental setup

Projects	Environment
Operating System	Windows 10(x64)
CPU	i5-9500HF CPU@2.40GHz
Memory Size	32GB
GPU	NVIDIA GeForce GTX 2080 Ti
CUDA Version	10.2
Python Version	3.8
Episode count Batch size Convergence criteria	1000 64 Training stops when reward, loss, episodes, or epsilon criteria are met.

4.1 Confusion matrix

The results of the confusion matrix are shown in Figure 6. The model accurately predicted all classes: 152 samples as class 0, 777 as class 1, and 71 as class 2, with zero misclassifications. This indicates that the energy management model is highly effective in correctly categorizing vehicle energy efficiency levels or strategies with no false positives or negatives across all classes. The predicted classes represent EMS efficiency levels: 0 (High), 1 (Medium), and 2 (low).

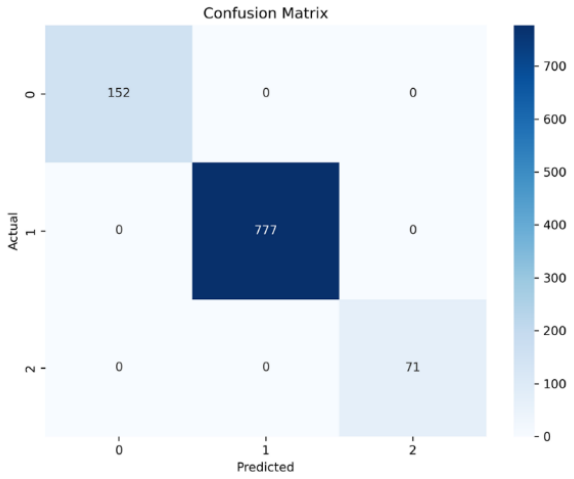

Figure 6: Confusion matrix outcomes

4.2 Battery degradation distribution

The distribution of battery degradation in NEV highlights a concentration of around 10%. It suggests significant wear under certain conditions, necessitating a dynamic energy management strategy. By integrating real-time degradation data, NEVs can optimize engine-battery energy distribution, extend battery life, and improve energy efficiency, especially under high-degradation scenarios. It supports adaptive, data-driven decision-making for sustainable vehicle performance. Figure 7 presents the distribution of battery degradation outcomes.

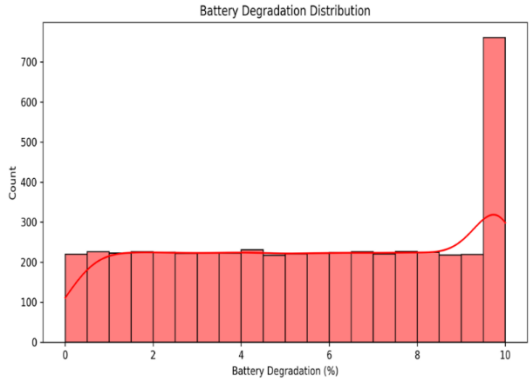

Figure 7: Distribution of battery degradation outcomes

4.3 WLTC

The EMS optimization results under the WLTC driving cycle show that the proposed SSB-MADQN method outperforms the existing method, MADDPG. SSB-MADQN achieves a higher terminal SOC (0.643 vs. 0.598), lower equivalent fuel consumption (0.912 L vs. 0.977 L), and improved fuel efficiency (3.864 L/100km vs. 4.199 L/100km), demonstrating its effectiveness in dynamic energy management for NEVs by enhancing energy utilization and reducing fuel use. Figure 8 presents the EMS optimization under WLTC.

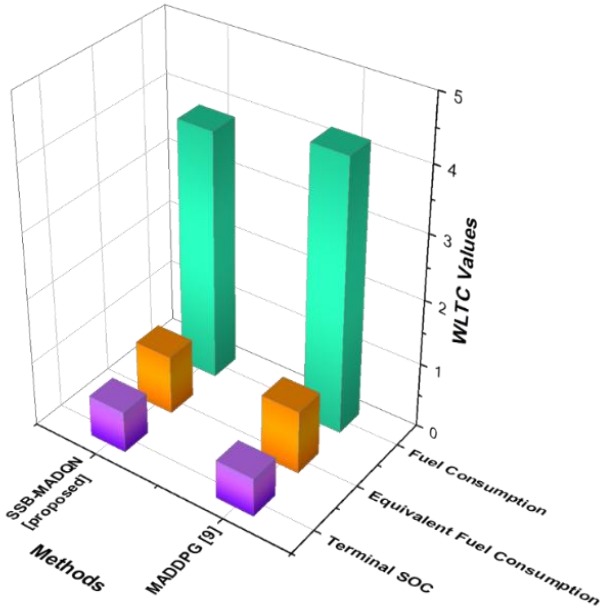

Figure 8: Graphical representation of WLTC

4.4 HWFET

According to the HWFET driving cycle, SSB-MADQN performs better than MADDPG when optimizing the EMS system. It achieves a higher terminal SOC (0.603 vs. 0.556), reduced equivalent fuel consumption (0.681 L vs. 0.734 L), and better fuel efficiency (4.121 L/100km vs. 4.446 L/100km), indicating improved energy recovery and reduced fuel usage in dynamic energy management for NEVs. Figure 9 presents the EMS optimization under HWFET.

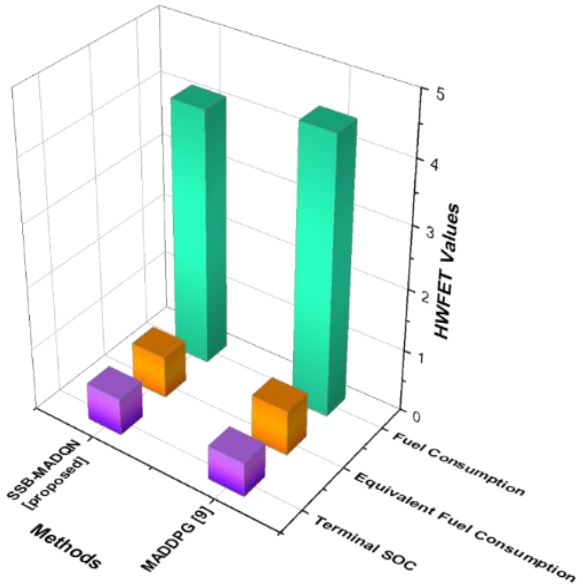

Figure 9: Graphical Representation of HWFET

4.5 Control action

A comparison of control action variations over time in dynamic energy management for NEVs. DQL-AMSGrad shows fluctuating control values, peaking at 1.5, indicating moderate adaptability. The proposed SSB-MADQN model consistently yields slightly higher control actions, with smoother transitions and a peak of 1.7, reflecting improved responsiveness and stability. It suggests SSB-MADQN's superior performance in managing energy distribution dynamically and efficiently in NEV systems. Table 4 and Figure 10 show control action outcomes.

Table 4: Control action outcomes

Model	10	20	30	40	50	60	70	80	90	100
DQL-AMSGrad [16]	1.3	0.4	0.3	1.0	0.1	0.8	1.2	1.5	0.1	0.3
SSB-MADQN [proposed]	1.5	0.6	0.7	1.2	0.2	1.0	1.4	1.7	0.3	0.6

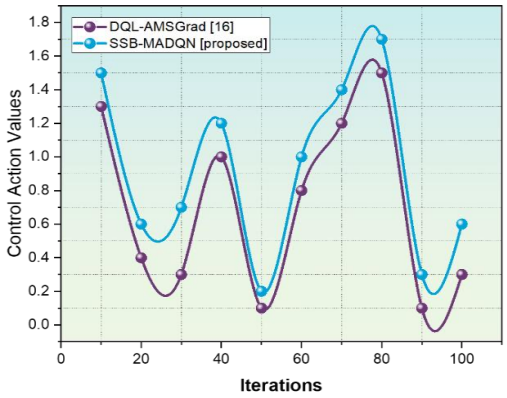

Figure 10: Graphical representation of control action

4.6 Performance metrics summary of SSB-MADQN for NEV energy management

The primary performance metrics of the proposed multi-agent deep reinforcement learning framework applied to dynamic energy management in new energy vehicles (NEVs). Metrics include fuel consumption, battery SOC limits, battery degradation rate, and computational efficiency during both training and real-time inference. These results demonstrate the framework's effectiveness in balancing energy usage and system longevity. Table 5 displays the SSB-MADQN performance.

Table 5: Key results of SSB-MADQN performance

Performance metric	SSB-MADQN (Proposed)
Fuel Usage	3.4 L/100km
SOC Bounds	20% – 80%
Degradation Rate (%)	0.72%
Training Time	4.1 hours
Inference Time	14 ms

5 Comparative analysis with existing systems

A dynamic EMS for NEVs optimizes power distribution between the battery and engine in real-time, enhancing energy efficiency, reducing emissions, and adapting to varying driving conditions. MADDPG faces limitations in scalability and convergence stability when managing complex multi-agent interactions in dynamic NEV energy environments. Such technology mandates a large amount of training
material alongside powerful computing capabilities. The integration of DQL-AMSGrad with adaptive learning rates facilitates better convergence, but it performs poorly with the continuous action spaces regularly found in NEV energy systems. The decision-making processes of these

methods show poor adaptation to sudden driving condition changes, along with restricted performance across different driving cycles, which affects real-time decisions in NEVs. The proposed SSB-MADQN enhances scalability and convergence stability by integrating the SSB with MADQN, enabling efficient exploration and exploitation in complex NEV environments. The system successfully deals with complex action spaces together with dynamic driving conditions because it learns quickly and provides reliable real-time energy management functionality that outperforms MADDPG and DQL-AMSGrad by showing better adaptability and generalization over several driving cycles. The proposed strategy relies heavily on high-quality simulations, which may not fully capture real-world complexities. Additionally, there is a lack of real-world validation, and the interpretability of multi-agent reinforcement learning models remains a challenge, hindering broader practical adoption.

6 Conclusion

Energy efficiency and operational performance in NEVs have significantly improved through the application of AI-driven optimization strategies. The suggested SSB-MADQN architecture used MARL to allow cooperative agents to control the engine and battery's power allocation in real time under various driving circumstances. Data preprocessing methods, such as data cleaning and min-max normalization, and PCA employed for feature extraction, ensured consistency, reduced dimensionality, and enhanced model learning. Experimental results revealed notable improvements, with fuel consumption reduced under WLTC compared to MADDPG, achieving a final consumption of 3.864 L/100km, and similarly under HWFET with a reduction to 4.121 L/100km. These outcomes confirm the effectiveness of intelligent EMS in achieving adaptive and globally optimized energy strategies for NEVs. The limitations of relying solely on simulation-based testing and plans to incorporate real-world ECU-in-the-loop evaluation to enhance validation. Another key challenge is the interpretability of the MARL model, for which we plan to adopt explainability techniques such as SHAP or LIME to analyze Q-values and better understand agent decisions. Additionally, potential deployment on edge computing platforms like NVIDIA Jetson is being considered to assess real-time feasibility. The proposed approach shows strong potential for real-time EMS in NEVs by leveraging decentralized agents and a powerful optimizer for high-dimensional spaces. However, to strengthen its scientific contribution, future work should focus on improving algorithm transparency, ensuring rigorous experimentation, and incorporating advanced statistical techniques for deeper validation and performance comparison.

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Hybrid Machine Learning and Optimization Algorithms for pH-Based Water Quality Classification

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Keywords: water quality, PH level, machine learning, support vector classifier, extra trees classifier, optimization algorithms

Received: December 2, 2024

Water quality—defined through its physical, chemical, and biological parameters—is essential for critical applications such as drinking and irrigation. Among these parameters, pH plays a significant role by influencing metal solubility and nutrient availability, thereby impacting aquatic ecosystems. In this study, Support Vector Classifier (SVC) and Extra Trees Classifier (ETC) were employed to classify water quality based on pH values. To boost classification accuracy, the models were hybridized using two advanced metaheuristic algorithms: Transit Search Optimization Algorithm (TSOA) and Chaos Game Optimization (CGO), resulting in hybrid variants ETTS, ETCG, SVTS, and SVCG. Comprehensive experiments were conducted using standard evaluation metrics. The ETTS model achieved the best performance, with training accuracy of 0.910 and testing accuracy of 0.778, along with a precision of 0.911, recall of 0.910, and F1 score of 0.910 in training. In contrast, the base ETC model recorded training and testing accuracies of 0.881 and 0.750, respectively. Similarly, SVTS and SVCG outperformed the base SVC model, with SVTS achieving training and testing accuracies of 0.894 and 0.760, compared to SVC's 0.850 and 0.745. The proposed hybrid framework outperforms traditional SVC and ETC models and demonstrates superior classification performance compared to standard non-optimized baselines. This underscores the value of integrating advanced optimization techniques with machine learning for robust and reliable water quality assessment. The framework is a promising tool for environmental monitoring, promoting sustainable water resource management and public health protection.

Povzetek: Študija je razvila hibridne modele strojnega učenja za klasifikacijo kakovosti vode na podlagi pH-vrednosti. Kombinacija klasifikatorjev Extra Trees (ETC) in Support Vector Classifier (SVC) z metahevrističnimi algoritmi TSOA in CGO (npr. ETTS, SVTS) je izboljšala klasifikacijo. Model ETTS je dosegel najboljšo zmogljivost, kar potrjuje prednost hibridnega okvira za okoljsko spremljanje.

1 Introduction

1.1 Background

Water is as familiar a material as air, earth and concrete, Water is necessary for life for humans and other forms of life, much like the other three materials—well, maybe with exception of concrete. It is voluminous: about 3.5 % of the land area is permanently flooded, whereas two thirds of the world is under the oceans. About the hydrosphere, water is continuously evaporating from the Earth's surface into condensing in the atmosphere, reappearing as liquid. Earth's supply of water is now at an all-time high and will never be depleted [1]. Although abundant, the water resources distributed unevenly in different regions in some serious respects impede certain regions. As the population rises, industrialization increases, and even more factors such as climate change enhance problems relating to water shortages or pollution. Efficiency in water management and water quality prediction plays an important role in ensuring safety and sustainability in the use of water [2]. These are some of the issues that emanate from a lack of adequate hydrological cycles, methods of water management, and knowledge concerning the various human activities impacting catchments of water. To this end, technological and policy development remains highly critical to ensure the sustainability of the use and delivery of water, protection of public health, and economic development [3].

Water quality is basically related to its physical, chemical, and biological characteristics, making it suitable for various purposes, such as drinking, gardening, and leisure activities. During any water quality assessment, turbidity, the microbiological content, and concentrations of both organic and inorganic compounds are amongst the

more commonly measured parameters [4]. The degradation of water quality is a consequence of the current process of urbanization, agricultural runoff, and industrial wastes. Some contaminants such as heavy metals, pesticides, and viruses may result in serious human health hazards and ecosystem health. Good water grading control will require technological advancement, community participation, and regulatory mechanisms. The implementation of best practices in pollution prevention, wastewater treatment, and watershed management will ensure the sustainability of water resources through better maintenance of their quality [5].

One of the factors influencing the pH of water and hence its chemical behavior and its biological availability is the concentration of hydrogen ions in it. Basically, pH is the measure of the concentration of hydrogen ions in water. It runs on a scale from 0 to 14, with 7 to 8 being considered neutral, 0 to 7 considered acidic, and 8 to 14 considered basic. PH influences the solubility of metals and nutrients' availability, along with activity concerning aquatic organisms.

Machine learning, as a multidisciplinary subset of artificial intelligence, develops algorithms with which computers can evaluate, comprehend, and predict data [6–9]. It has powerful capabilities for identification, data analysis, and decision making and has already revamped many disciplines. The application of machine learning techniques is on the increase in environmental research to enhance our understanding and management through the modeling of environmental processes, analysis of large-scale information, and predictions of future conditions [10]. The most promising application would, therefore, be in the monitoring of water quality through management using machine learning. With the derivation of large data sets from sensors and satellite images, coupled with historical records, it will be possible for machine learning models to develop leading trends, anomalies, and predictions of water quality parameters with high accuracy [11] [12]. These capabilities enable more proactive and effective water management strategies, reducing pollution, optimizing resource allocation, and protecting public health. The integration of machine learning into the water quality monitoring system is one of the huge leaps forward in environmental science and technology [13] [14].

1.2 Research gaps and objectives

Despite the increasing application of ML in water quality prediction, significant challenges persist. Traditional approaches often struggle with the nonlinearity and complex variability of environmental data, which limits their predictive accuracy and generalizability across diverse contexts. Furthermore, while various studies have employed models like MLR, ANN, and SVM, many lack the integration of robust optimization algorithms to fine-tune model parameters and enhance performance.

Another notable gap is the underutilization of ensemble tree-based methods such as the ETC, which are known for their resilience to noise and their ability to capture intricate relationships within high-dimensional datasets. Additionally, real-time pH prediction, a critical parameter in assessing water quality, has not been extensively explored using hybrid ML-optimization techniques, especially in scenarios where both historical and real-time data are available.

To address these gaps, this study proposes a novel framework that integrates SVM, ETC, TSOA and CGO. These techniques are applied to predict and classify water pH levels using historical and sensor-based real-time datasets. The objectives of this research are:

- To develop and compare ML models capable of accurately predicting water pH levels using both historical and real-time input data;
- To optimize model performance using the Chaos Game Optimization algorithm, ensuring more reliable and efficient learning from complex datasets;
- To evaluate the classification capabilities of the Extra Trees Classifier and SVM in distinguishing water quality categories based on pH thresholds;
- To demonstrate the feasibility of a hybrid ML-optimization approach for proactive and sustainable water quality monitoring.

2 Related works

Idroes et al. [15] conducted a study to predict urban air quality in DKI Jakarta, Indonesia, using the CATBoost machine learning algorithm, which is known for handling categorical features effectively, managing missing values, and reducing the risk of overfitting. The research utilized air quality data collected from Jakarta's monitoring stations over the period of 2010 to 2021. The dataset included five key pollutants: PM_{10}, SO_2, CO, O_3, and NO_2. After a preprocessing stage that involved data cleaning and normalization, the authors split the dataset into training (80%) and testing (20%) subsets. The CATBoost model was trained and evaluated using standard performance metrics, where it achieved high accuracy (0.9781), precision (0.9722), and recall (0.9728). A feature importance analysis revealed that ozone (O_3) was the most significant contributor to air quality variation, followed by PM_{10}. Sasmita et al. [16] investigated the classification of air quality levels in Indonesia using the Plume Air Quality Index (PAQI), which incorporates pollutant concentrations such as $PM_{2.5}$, PM_{10}, NO_2, and O_3. The study focused on evaluating classification performance using Decision Tree and K-Nearest Neighbor (k-NN) algorithms, applied to secondary data collected from 33 provincial capitals between July 1 and December 31, 2022. Unlike prior studies that typically assessed model performance solely based on accuracy, this research adopted a more comprehensive evaluation approach by incorporating precision, recall, and F1-score alongside accuracy. The results demonstrated that the Decision Tree classifier outperformed k-NN, achieving performance scores of 90.67% accuracy, 90.61% precision, 90.67% recall, and 90.63% F1-score. These findings suggest that tree-based models can provide robust classification capabilities for air quality indexing, supporting more reliable monitoring and decision-making

regarding urban environmental health. Putra et al. [17] addressed the critical issue of deteriorating air quality in Indonesia's major cities, with a focus on Jakarta, where urbanization and anthropogenic activities such as vehicular emissions, industrialization, and waste accumulation have significantly impacted atmospheric conditions. Their study aimed to classify daily air quality using machine learning algorithms—specifically the C5.0 algorithm and Random Forest—based on the Air Pollution Standard Index (ISPU). These models were applied to datasets from 2017 and 2018, consisting of pollutant parameters including CO, NO_2, SO_2, PM, O_3, and NO. Their classification approach emphasized the importance of accurately identifying air quality categories to support policy-making. The models demonstrated high predictive accuracy, with C5.0 and Random Forest achieving 99.74%, 99.22%, and 99.97% accuracy on the 2017 dataset and 98.28%, 98.85%, and 97.42% on the 2018 dataset, respectively. The analysis identified O_3 (ozone) as the most influential factor in classifying air quality, with most days falling under the "Moderate" ISPU category. This work highlights the potential of decision tree-based algorithms in supporting urban air quality management through accurate pollutant classification. Saxena and Shekhawat [18] proposed a novel mathematical framework to compute a Cumulative Index (CI) for air quality classification based on the concentrations of four major pollutants: SO_2, NO_2, PM2.5, and PM10. This CI served as a compact, interpretable metric reflecting the combined impact of pollutants on air quality. Using these CI values as input features, they developed a two-class Support Vector Machine (SVM) model to classify air quality as either *good* or *harmful*. To optimize the performance of the SVM, the authors employed the Grey Wolf Optimizer (GWO) for parameter tuning, aiming to maximize classification accuracy. The methodology was tested on real datasets from three major Indian cities—Delhi, Bhopal, and Kolkata. The results indicated that the proposed classifier effectively distinguished between the two air quality categories, with high classification performance across all test locations. The study concluded that the CI-based classification framework was both computationally efficient and aligned well with actual air quality data, making it a promising tool for public health and environmental monitoring. The summary of the previous studies reported in Table 1.

Table 1: The summary of the related works.

Study	Methodology	Dataset	Metrics' results	Key Findings
Idroes et al. [15]	CATBoost machine learning for air quality prediction.	Air quality data from Jakarta monitoring stations (2010-2021). Pollutants: PM_{10}, SO_2, CO, O_3, NO_2.	Accuracy: 0.9781, Precision: 0.9722, Recall: 0.9728	Ozone (O_3) and PM_{10} most significant pollutants.
Sasmita et al. [16]	Classification using Decision Tree and k-NN algorithms.	Secondary data from 33 provincial capitals in Indonesia (2022). Pollutants: $PM_{2.5}$, PM_{10}, NO_2, O_3.	Accuracy: 90.67%, Precision: 90.61%, Recall: 90.67%, F1: 90.63%	Decision Tree outperformed k-NN for classification tasks.
Putra et al. [17]	Classification using C5.0 and Random Forest algorithms.	Air quality data (2017-2018). Pollutants: CO, NO_2, SO_2, PM, O_3, NO.	C5.0: 99.74% (2017), 98.28% (2018), RF: 99.22% (2017), 98.85% (2018)	Ozone (O_3) as the most influential factor in classifying air quality.
Saxena and Shekhawat [18]	Support Vector Machine (SVM) classification with Grey Wolf Optimizer (GWO) for parameter tuning.	Real datasets from three Indian cities (Delhi, Bhopal, Kolkata). Pollutants: SO_2, NO_2, $PM_{2.5}$, PM_{10}.	Classification performance: High accuracy for all test locations	CI-based classification framework is computationally efficient.

3 Materials and methodology

3.1 Data gathering

Water quality data were collected in a systematic manner and analyzed for different environmental parameters and their relations to pH values. The dataset used in the present study derived from [19] incorporates 1320 records in total, and each of the following input parameters has been included in the dataset: Date, Salinity, Dissolved Oxygen, Secchi Depth, Water Depth, Water Temperature, and Air Temperature. The output variable analyzed here is the pH level of the water, whether it be basic, alkaline, or acidic. Data recording over some period gathered daily data on water quality. In this case, the 'Date' variable provides for the exact day (a day in every two weeks) certain data was taken and offers a time-series track showing environmental change over time. Salinity, representing the concentration of dissolved salts in water, can directly influence pH levels by altering the ionic balance and buffering capacity of the water body. Variations in salinity may therefore contribute to shifts in pH, particularly in estuarine and coastal environments. Dissolved oxygen (DO), essential for aquatic life, can also impact pH through biological processes such as respiration and

photosynthesis, which either consume or release CO_2, thereby influencing acidity. Secchi Depth, a measure of water transparency determined by noting the depth at which a Secchi disk disappears, can serve as an indirect indicator of photosynthetic activity, which affects CO_2 levels and thus the pH. Water Depth at the sampling location affects both light availability and thermal stratification, which can influence biological activity and chemical reactions that regulate pH. Water Temperature and Air Temperature offer insight into thermal conditions that affect metabolic rates of organisms and chemical equilibria, both of which can influence pH values. The primary focus of this study was on pH levels, a key parameter in assessing water quality. In the dataset, pH values were categorized and analyzed as follows: Acidic (pH < 7) with 433 instances, Neutral (pH = 7) with 617 instances, and Basic (pH > 7) with 280 instances. Each of the variables was examined in relation to these pH categories to explore their predictive relevance.

Figure 1. consists of several parallel plots, the $x-axis$ in each plot represents the total number of samples, providing a consistent framework for comparing the distribution of each parameter. $The\ y-axis,\ varies$ according to the parameter being measured, showing the specific quantity for each sample. The red dots effectively illustrate the range and concentration of values for each parameter, offering an unambiguous graphic depiction of the data's distribution. For instance, the clustering of red dots below 0.4 meters for water depth highlights that most water samples were taken from shallow depths, with deeper samples being rare. The output pH plot illustrates the red dots form distinct horizontal bands, suggesting that pH measurements are discrete rather than continuous. This discrete distribution is crucial for classifying water quality based on pH levels.

To support the development and execution of the proposed models, a high-performance desktop workstation was utilized. This system is equipped with an Intel® Core™ i7-3770K processor clocked at 3.50 GHz and complemented by 16 GB of RAM, ensuring efficient processing and multitasking capabilities. The operating system used was Windows 11 Pro (64-bit), running on an x64-based architecture. Visual computations and graphical rendering were handled by an NVIDIA GeForce GT 640 graphics card, which contributed to a responsive and stable graphical environment. A 1 TB internal hard disk served as the primary storage medium, providing ample space for managing datasets and associated files.

All programming tasks were conducted using Python. The scikit-learn library formed the foundation for building and assessing machine learning algorithms. Data preparation and numerical analysis were facilitated by Pandas and NumPy, respectively. To aid in visual interpretation of results, Matplotlib was employed, enabling clear and informative graphical outputs throughout the analysis process.

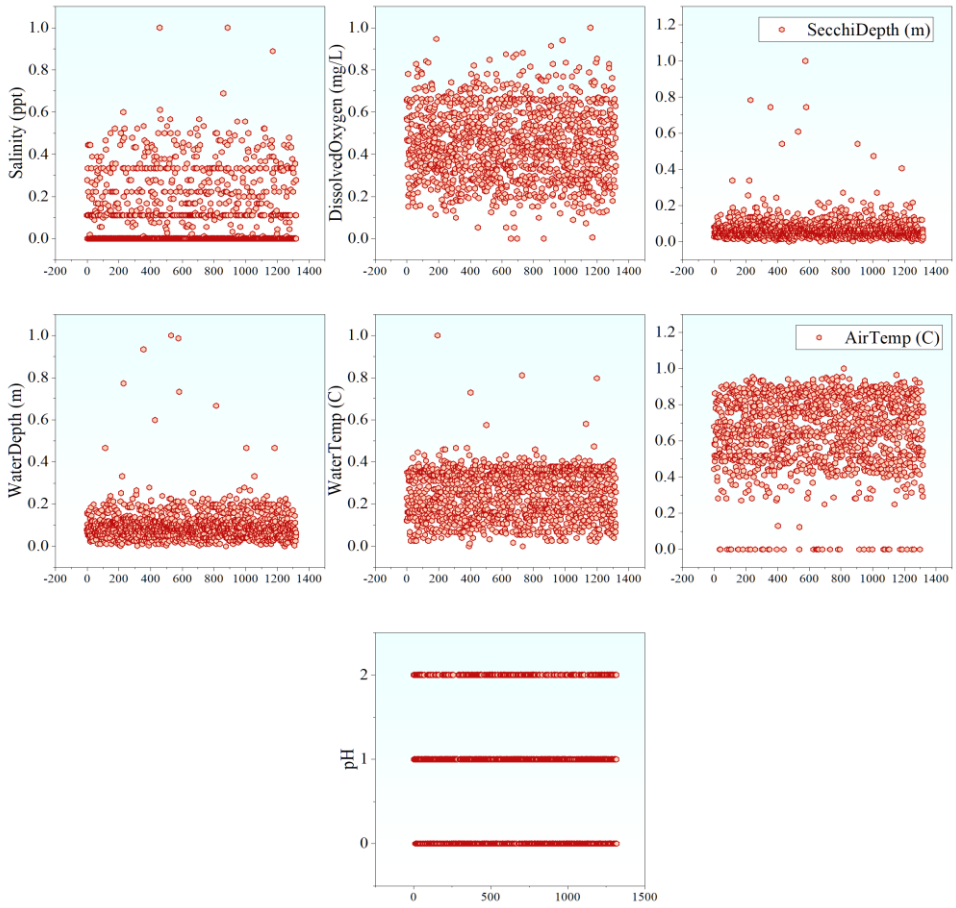


Figure 1: The parallel plot of the inputs and outputs variables

3.2 Support vector classification

Support Vector Classification (SVC) is a supervised learning algorithm rooted in the structural risk minimization principle of Support Vector Machines (SVM) [20]. It operates by mapping input features into a higher-dimensional space through non-linear kernel transformations, enabling the separation of data that is not linearly separable in the original feature space. In this transformed space, SVC constructs an optimal hyperplane that maximizes the margin — defined as the distance between the hyperplane and the closest data points from each class, known as support vectors — while simultaneously minimizing classification errors [21]. This balance between margin maximization and error minimization contributes to the model's generalization capability and robustness.

$$min_{w,b,\epsilon} \frac{\|W\|^2}{2} + C_{svc} \sum_{i=1}^{N} \epsilon_i \quad (1)$$

$$y_i(w^T.\emptyset(x_i) + b) \geq 1 - \epsilon_i \qquad i = 1,\ldots,N \quad (2)$$

$$\epsilon_i \geq 0 \qquad i = 1,\ldots,N \quad (3)$$

The function $\emptyset(x_i)$ represents a nonlinear mapping that projects each input observation x_i, defined by its explanatory variables, into a higher-dimensional feature space where linear separation of classes becomes more feasible. Within this space, w denotes the weight vector that defines the orientation of the separating hyperplane, while b is the bias term that shifts the hyperplane to achieve optimal separation. The parameter C_{svc} serves as a regularization factor that balances the trade-off between maximizing the margin and minimizing classification errors. The slack variables ϵ_i quantify the degree to which individual observations violate the margin constraints, allowing for soft-margin classification to accommodate misclassified or non-linearly separable data points.

Determining the optimal hyperplane, as formulated in Eq. (4), entails maximizing the margin between classes in the high-dimensional feature space. This objective is mathematically achieved by minimizing the Euclidean norm of the weight vector, which directly corresponds to maximizing the margin width. Simultaneously, the model incorporates a penalty for misclassified instances to ensure a balance between model complexity and classification accuracy. Ultimately, the predicted output labels indicate the class membership of each sample, based on their position relative to the decision boundary.

$$D(x_i) = W^T \varphi(x_i) + b \quad (4)$$

The computational complexity of the primal formulation is primarily dependent on the number of input features (dimensionality), whereas the dual formulation's complexity scales with the number of training samples. Therefore, in scenarios involving high-dimensional feature spaces, it is often more computationally efficient and advantageous to employ the dual form of the model, as outlined in Eqs. (5–7).

$$max_a \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{i=1}^{N} a_i a_j y_i y_j K(x_i, x_j) \quad (5)$$

$$\sum_{i=1}^{N} a_i y_i = 0 \quad (6)$$

$$0 \leq a_i \leq C_{svc} \qquad i = 1,\ldots,N \quad (7)$$

A kernel function, denoted as $K(x_i, x_j)$, computes the inner product between pairs of input samples implicitly mapped into a high-dimensional feature space, enabling nonlinear classification without explicitly performing the transformation. Common kernel types include linear, polynomial, radial basis function (RBF), and sigmoidal kernels, among others. For a kernel to be valid, it must satisfy Mercer's conditions—specifically, it must be symmetric and positive semi-definite. Extensive studies have shown that the RBF kernel, formally defined in Eq. (8), is particularly effective for classification problems due to its localized response and flexibility. Accordingly, the RBF kernel is adopted in our methodology, where the hyperparameter γ governs the inverse of the squared radius of influence of the support vectors, effectively controlling the decision boundary's smoothness and sensitivity to individual data points.

$$K(x_i, x_j) = \emptyset(x_i)^R \emptyset(x_j) = exp(-\gamma \|x_j - x_i\|) \quad (8)$$

Once the optimization process is completed and the optimal weight vector and bias term are obtained, the trained model can be used to generate predictions for unseen samples by evaluating the decision function as defined in Eq. (9).

$$SVC \quad y_i = \begin{cases} -1 \; if \; w^T \emptyset(x_i) + b \; \leq 0 \\ 1 \; if \; w^T \emptyset(x_i) + b \; > 0 \end{cases} \quad (9)$$

3.3 Extra trees classifier

The Extra trees classifier, proposed by Geurts et al. [22], represents an advanced ensemble learning technique that builds upon and extends the Random Forest framework. Unlike traditional ensemble methods that rely on bootstrapped datasets and deterministic split criteria, Extra Trees introduces two levels of randomness to enhance model diversity and generalization. First, it selects split thresholds at random rather than searching for the most optimal ones. Second, instead of using bootstrap sampling, it grows each decision or regression tree using the entire training dataset. This approach not only accelerates the training process but also reduces variance, making Extra Trees particularly effective for high-dimensional and noisy datasets.

Extra Trees operates by introducing controlled randomness into the decision tree construction process, particularly for numerical features. At each node, the algorithm selects K random features and determines split thresholds uniformly at random, rather than through traditional optimization. The minimum number of samples required to allow further splitting is defined by n_{min}, ensuring regularization. Unlike methods that rely on bootstrap resampling, Extra Trees trains each of its M trees on the entire original dataset, promoting stability and minimizing bias. For prediction, the ensemble outputs are combined using majority voting in classification tasks or averaged in regression settings. This explicit

randomization strategy—both in attribute selection and cut-point determination—significantly reduces variance and enhances generalization performance, especially in high-dimensional and noisy contexts. Although the algorithm exhibits a time complexity of $N \log N$, its computational efficiency is bolstered by the lightweight nature of the node-splitting process. The key hyperparameters—K, n_{min}, and M—govern the diversity of splits, regularization, and ensemble size, respectively. While the algorithm supports fine-tuning, default parameter configurations often yield strong performance, making Extra Trees both effective and computationally autonomous.

3.4 Chaos game optimization

The amalgamation of basic principles of chaotic games and fractals provide a mathematical model for the algorithm CGO [23]. The CGO algorithm examines several potential solutions (X) for this goal, that depicts a few suitable seeds within a sierpinski triangle, so that a group of answers that have developed by chance and selection changes is maintained by many natural evolution algorithms. According to this technique, a few chosen variables $(x_{i,j})$ reflect where these eligible seeds are located inside the triangle formed by sierpinski. with every potential solution (X_i).

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^j & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^j & \cdots & x_2^d \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^j & \cdots & x_i^d \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^j & \cdots & x_n^d \end{bmatrix} \quad (10)$$

According to the sierpinski triangle, where n is the number of eligible seeds and d is the seed's dimension. Based on random starting positions, these qualifying seeds are arranged in the search space.

$$x_j^j(0) = x_{i,min}^j + rand.\left(x_{i,max}^j - x_{i,min}^j\right), \quad \begin{cases} i = 1, 2, \ldots, n. \\ j = 1, 2, \ldots, d. \end{cases} \quad (11)$$

In this approach, $x_j^j(0)$ represents the initial position of qualified seeds. The values $x_{i,min}^j$ and $x_{i,max}^j$ define the lower and upper bounds for the jth decision variable of the ith candidate. A random number between 0 and 1 guides the movement direction.

Qualified seeds symbolize core concepts from chaos theory. These seeds represent candidate solutions in an optimization problem, where higher and lower fitness values indicate better and worse suitability, respectively.

To explore the search space, qualified seeds are used to construct a Sierpinski triangle—a structure made from three points: the current candidate (X_i), the group mean (MG_i), and the global best (GB). This triangle is a basis for generating new seeds using a chaos game approach.

Each triangle uses a virtual die with green and red faces to decide movement: green directs the seed toward the global best (GB), and red toward the group mean (MG_i). A random binary value (0 or 1) determines the face. This process allows seeds to move stochastically within the search space, with randomness and minimal movement controlled using factorial-based adjustments.

$$Seed_i^1 = x_i + \alpha_i \times (\beta_i \times GB - MG_i), \quad i = 1, 2, \ldots, n. \quad (12)$$

Assuming that X_i represents theith potential solution and the randomly generated factorial used to describe the limitations of seeds on movement is called α_i. To simulate the potential to roll a pair of dice β_i and γ_i stand for a random number of $0\ or\ 1$.

$$Seed_i^2 = GB + \alpha_i \times (\beta_i \times X_i - \gamma_i \times MG_i) \quad (13)$$

$$Seed_i^3 = MG_i + \alpha_i \times (\beta_i \times X_i - \gamma_i \times GB), \quad i = 1, 2, \ldots, n. \quad (14)$$

A fourth seed is produced by using an additional technique to carry out the mutation phase in the search space's position updates of the qualified seeds. This update of the seed's position is based on arbitrary modifications to the choice variables chosen at random.

$$Seed_i^4 = X_i\left(x_i^k = x_i^k + R\right), \quad k = [1, 2, \ldots, d]. \quad (15)$$

A random integer in the interval $[1, d]$ is denoted by k, and R is a uniformly distributed random number in the region $[0,1]$.

The CGO algorithm's exploration and exploitation rate can be controlled and modified by varying the movement limits of the seeds, represented by four different formulations for α_i.

$$\alpha_i = \begin{cases} Rand \\ 2 \times Rand \\ (\delta \times Rand) + 1 \\ (\varepsilon \times Rand) + (\sim \varepsilon) \end{cases} \quad (16)$$

In this case, δ and ε are random integers Rand is a random number with a uniform distribution in the interval $[0,1]$.

The process involves evaluating new seeds against existing ones to determine their eligibility for inclusion within the area used for searching. The new solution candidates' quality is evaluated, with better candidates retained and seeds with low fitness values removed. The replacement procedure is employed to simplify the mathematical model and ensure a more efficient mathematical method.

3.5 Transit search algorithm

Host star number (n_s) and the definition of signal-to-noise ratio (SN) is algorithm structure. The transit model determines SN Standard deviation of measurements made outside of transit is used to estimate noise. There is always noise in photons received from stars. The starting population for TS is equal to the product of n_s and SN [24].

- **Galaxy phase**

After identifying habitable zones, the program chooses a galactic center at random from the search space. The optimal stellar systems are found by evaluating random regions L_R. With the capacity to support life, the regions that have been identified with the best fitness are chosen, and the algorithm starts with these regions.

$$L_{R,l} = L_{Galaxy} + D - Noise \quad l = 1, \ldots, (n_s \times SN) \quad (17)$$

$$D = \begin{cases} c_1 L_{Galaxy} - L_r & if \quad z = 1 \quad (Negative\ Region) \\ c_1 L_{Galaxy} + L_r & if \quad z = 2 \quad (Positive\ Region) \end{cases} \tag{18}$$

$$Noise = (c_2)^3 L_r \tag{19}$$

L_{Galaxy} denotes where the center of the galaxy is located, and in the optimization problem, two coefficients are present ranging from $zero$ to one, denoting an accidental integer c_1 and an accidental vector c_2 representing the number of variables. To demonstrate the variation in the research area's situation, one definition of parameter D is the difference between the galaxy's center and its present condition. This region may be found either on the back of the galaxy or in the front (positive portion) of its middle area. Here, parameter zone (z) is a randomly generated number that is either one or two. The $Noise$ parameter is used to eliminate noise from received signals to improve location accuracy. To minimize computational value, the coefficient c_2 with a power of 3 is used, as noise cannot noticeably deviate from desired situations.

$$L_{s,i} = L_{R,i} + D - Noise \quad i = 1, \dots, n_s \tag{20}$$

The light spectrum (star class) that the telescope receives and the star's distance from the observer may be used to determine the luminosity of the star. It is evident that a short distance results in a higher photon count. The star's luminosity is acquired by:

$$L_i = \frac{\frac{R_i}{n_s}}{(d_i)^2} \quad i = 1, \dots, ns \quad R_i \in \{1, \dots, n_s\} \tag{23}$$

$$d_i = \sqrt{(L_s - L_T)^2} \quad i = 1, \dots, ns \tag{24}$$

Here, Star I's luminance and rank are depicted by the variables L_i and R_i. Additionally, the space between the star I and the telescope are covered by d_i. Since it is chosen at random at the beginning of the method, the location of the telescope L_T remains constant throughout the optimization.

$$L_{S,new,i} = L_{S,i} + D - Noise \quad i = 1, \dots, n_s \tag{25}$$

$$D = c_6 L_{S,i} \tag{26}$$

$$Noise = (c_7)^3 L_S \tag{27}$$

The coefficients c_6 and c_7 are a random vector from 0 to 1 and a random integer from -1 to 1. The amount of new luminosity, $L_{i,new}$ is determined by:

$$L_{i,new} = \frac{R_{i,\frac{new}{n_s}}}{\left(d_{i,new}\right)^2} \quad i = 1, \dots, ns \tag{28}$$

The new L_S and the position of the telescope may be used to compute the parameter $d_{i,new}$. It is possible to assess the possibility of transit by comparing L_i and $L_{i,new}$. If $T = 1$, the phase of the planet is utilized; if not, the phase of the neighbor e is used in this iteration.

$$\begin{aligned} &If\ L_{i,new} < L_i \quad P_T = 1 \quad (Transit) \\ &If\ L_{i,new} \geq L_i \quad P_T = 0 \quad (No\ Ttansit) \end{aligned} \tag{29}$$

This probability P_T is represented by the numbers0 (non-transit) and 1 (probability of transit). If $P_T = 1$, if the planet phase cannot be used, this iteration uses the neighbor phase.

- **Planet Phase**

Initially, at this stage, the discovered initial position of planet is identified. The quantity of light that the telescope receives decreases during a planet's transit

$$D = \begin{cases} c_4 L_{R,i} - c_3 L_r & if \quad z = 1 \quad (Negative\ Region) \\ c_4 L_{R,i} - c_3 L_r & if \quad z = 2 \quad (Positive\ Region) \end{cases} \tag{21}$$

$$Noise = (c_5)^3 L_r \tag{22}$$

The next stage involves utilizing Eq. (20) to (22) to choose a star from each of the areas that have been chosen to belong to a stellar system. L_s indicates where the stars are located. In addition to the coefficient c_5, which is a random vector between 0 and 1, the coefficients c_3 and c_4 are random values between 0 and 1.

Before beginning iterations, the suggested method executes the galaxy phase once to choose appropriate situations for the primary stages (2– 5).

- **Transit Phase**

To identify the transit, a re-measurement of the light received from the beginning is required to identify any potential decrease in the received light signals. L_S and its corresponding fitness f_S have two meanings (M_1 and M_2). between the telescope and the star since the light comes from the star.

$$L_z = \frac{c_8 L_T + R_L L_{S,i}}{2} \quad i = 1, \dots, n_s \tag{30}$$

$$R_L = \frac{L_{S,new,i}}{L_{S,i}} \tag{31}$$

The planet's original position upon detection is demonstrated by L_z and luminance ratio is determined by R_L. Also, c_8 has a random value between 0 and 1.

$$L_{m,j} = \begin{cases} L_z + c_9 L_r & if \quad z = 1 \\ L_z - c_9 L_r & if \quad z = 2 \quad j = 1, \dots, SN \\ L_z + c_{10} L_r & if \quad z = 3 \end{cases} \quad \begin{matrix} f \\ fc \end{matrix} \tag{32}$$

$$L_P = \frac{\sum_{j=1}^{SN} L_{mj}}{SN} \tag{33}$$

To validate travel and reducing the noise's influence, one of the most crucial factors is SNThe planet's position inside its star system is specified by analyzing the quantity of signals received, which is derived from the planet's estimated position. Several SN signals are taken into account for this reason in the TS algorithm Eq. (32). The coefficient c_9 is an accidental number ranging from -1 to 1. c_{10} is a random vector with values in the range of -1 to 1. Once signals L_m have been determined, the average of SN signals are used to adjust the detected final planet position L_P. The terms Aphelion and Perihelion refer to the relative furthest and closest distances, in astronomy, between a planet (such as Earth) and the Sun or another host star. Three zones—Aphelion, Perihelion, and Neutral regions (the area between Aphelion and Perihelion areas), Eq. (32), are affected by the TS technique, which estimates the planet's orbital location using the zone parameter (z) in the planet phase.

- **Neighbor Phase**

In this phase, the present planet of the star will take its position whether the neighbor has superior circumstances compared to the current planet.

$$L_z = \frac{\left(c_{11} L_{s,new} + c_{12} L_r\right)}{2} \tag{34}$$

$$L_{n,j} = \begin{cases} L_z - c_{13}L_r & if \quad z = 1 \ \ for\ Aphelion\ region \\ L_z + c_{13}L_r & if \quad z = 2 \ \ for\ Perihelion\ region \\ L_z + c_{14}L_r & if \quad z = 3 \ \ for\ Neutral\ region \end{cases} \quad (35)$$

$$L_{N,i} = \frac{\sum_{j=1}^{SN} L_{n.j}}{SN} \quad (36)$$

Eq. (34) is used to estimate the neighbor L_z beginning position Considering its host star $L_{s,new}$ and an accidental place L_R. L_N determines the neighbor planet's ultimate position planets Eq. (35) and (36). The coefficients c_{11} and c_{12} in Eq. (41) handle a randomized integer in the range of 0 to 1. Moreover, the coefficients c_{13} and c_{14} represent a vector with a random number and a range of -1 to 1, respectively.

- **Exploitation phase**

The ideal planet for every star is identified in the earlier stages. Finding a planet by itself is meaningless. Understanding the features of the planet and the circumstances that support life is essential. This is carried out during the TS algorithm's Exploitation step. This stage expresses a revised definition of the L_P. L_P in the present phase L_E alludes to the features of the planet. Using Eq. (37), (38), the planet's ultimate properties are adjusted SN times $(j = 1, \ldots, SN)$ by adding new knowledge (K). c_{15} is an accidental number ranging from zero $to\ two$, and c_{16} is an accidental number ranging from $zero$ to one. c_{17} is an accidental vector ranging from zero to one. The knowledge index is represented by the random number c_k, which can be $1, 2, 3$, or 4. A random power between 1 and $(n_s * SN)$ is represented by P.

$$L_{E,j} = \begin{cases} c_{16}L_P + c_{15}k & if \quad c_k = 1 \quad (State\ 1) \\ c_{16}L_P - c_{15}k & if \quad c_k = 2 \quad (State\ 2) \\ L_P - c_{15}K & if \quad c_k = 3 \quad (State\ 3) \\ L_P + c_{15}K & if \quad c_k = 4 \quad (State\ 4) \end{cases} \quad (37)$$

$$K = (c_{17})^P L_r \quad (38)$$

3.6 K-Fold Cross validation

K-fold cross-validation is a widely utilized and reliable approach for evaluating and selecting models, especially in classification and regression tasks. This technique involves dividing the dataset into *k* equally sized subsets (folds). During each iteration, one-fold is reserved for validation while the remaining *k−1* folds are used for training. This process is repeated *k* times, ensuring that every subset serves once as the validation set. In this study, a 5-fold cross-validation scheme (*k = 5*) was adopted to thoroughly evaluate the proposed models and improve their generalization capability by systematically rotating the training and testing partitions. As illustrated in Fig. 2, the Support Vector Classifier (SVC) model demonstrated its peak performance during Fold 5, achieving a maximum Accuracy of 0.82. Similarly, the Extra Trees Classifier (ETC) also recorded its highest accuracy in Fold 5, with an Accuracy of 0.846, indicating consistent model performance across folds.

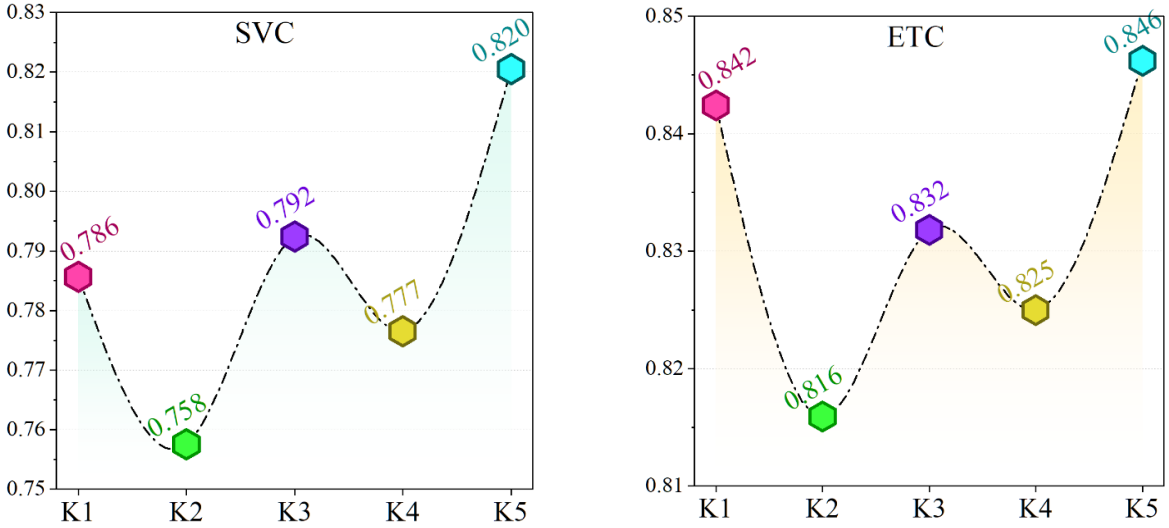


Figure 2: The results of 5-Fold Cross validation.

3.7 Evaluation metrics

The evaluation metrics of the classification models provide a quantitative measure of the performance of the models [25]. In this study, four fundamental evaluation metrics were employed to assess the performance of the classification models: Accuracy, Precision, Recall, and F1-score. These metrics provide a comprehensive understanding of model performance, especially in the context of imbalanced or complex classification problems.

- **Accuracy**

Accuracy is the ratio of correctly predicted observations to the total observations. It is a general measure of a model's effectiveness.

Accuracy serves as a baseline metric to understand the overall performance of the model. However, it may be misleading when dealing with imbalanced datasets, which is why complementary metrics are also considered.

- **Precision**

Precision is the ratio of correctly predicted positive observations to the total predicted positives. It reflects how well the model avoids false positives.

Precision is particularly valuable in scenarios were predicting a false positive may lead to unnecessary actions or costs.

- **Recall (Sensitivity)**

Recall is the ratio of correctly predicted positive observations to all actual positives. It shows how well the model detects actual positive cases. Recall is emphasized when it is more critical to identify all positive cases, even at the cost of some false positives.

- **F1-score**

The F1-score is the harmonic mean of Precision and Recall. It provides a single metric that balances both concerns, particularly useful when class distribution is uneven. The F1-score provides a consolidated metric for overall classification performance, particularly useful when neither precision nor recall alone is sufficient for model evaluation.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (39)$$

$$Precision = \frac{TP}{TP + FP} \quad (40)$$

$$Recall = \frac{TP}{TP + FN} \quad (41)$$

$$F1 - score = \frac{2.TP}{2.TP + FP + FN} \quad (42)$$

4 Result and riscussion

Prediction is actually something quite central to scientific research and practical decision-making, dealing with the estimation of the future state or event given current and historical data. Precise predictions are important in diverse fields such as meteorology to finance, for which the information furnished stands useful in planning, risk management, and policy development. Predictive models in environmental science are helpful and important to predict occurrences such as the spread of pollution, climate change, and water resource availability. The models are helpful in supporting sustainability management and conservation. Water quality prediction grounded on models such as ETC and SVC is among the most vital inputs into the planning and regulation of water quality.

Most advanced optimization techniques, such as $TSOA$ and CGO, have been employed in the enforcement of SVC and ETC for the much more improved classification of water quality according to pH. As a result, the base models ETC and SVC are involving the application of optimizers to constitute hybrid models such as $ETTS, ETCG, SVTS,$ and $SVCG$. Performance checking of the derived hybrid models is to be done for water quality prediction with respect to the pH level.

- **Hyperparameters' results**

In machine learning, hyperparameters are essential settings defined prior to training that influence model performance and learning behavior. Unlike trainable parameters, hyperparameters must be optimized to achieve the best results. In this study, random search was used to tune the hyperparameters of the proposed SVC- and ETC-based hybrid models.

As shown in Tables 2 and 3, ETC-based models were optimized using parameters such as n_estimators, max_depth, min_samples_split, min_samples_leaf, and max_leaf_nodes. For example, ETTS used n_estimators = 143 and max_leaf_nodes = 1431, while ETCG had higher values like n_estimators = 1805 and max_leaf_nodes = 17090.

SVC-based models were tuned with C and gamma. SVTS used C = 103.098, gamma = 138.373, while SVCG had C = 679.000, gamma = 111.500. The base SVC and ETC models retained simpler, default configurations. This tuning improved accuracy and computational efficiency across all hybrid models.

Table 2: The results of Hyperparameters for ETC-based hybrid models.

Models	**Hyperparameter**				
	n_estimators	max_depth	min_samples_split	min_samples_leaf	max_leaf_nodes
ETTS	143	143	0.001	0.000	1431
ETCG	1805	142	0.972	0.500	17090
ETC	100	None	2.000	1.000	None

Table 3: The results of Hyperparameters for SVC-based hybrid models.

Models	**Hyperparameter**	
	C	gamma
SVTS	103.098	138.373
SVCG	679.000	111.500
SVC	1.000	scale

- **Convergence curves**

Figure 3 illustrates the convergence curves of the proposed hybrid models, which combine machine learning classifiers (SVC and ETC) with metaheuristic optimization algorithms (TSOA and CGO). The figure captures the progression of classification accuracy across successive iterations, with the y-axis representing model accuracy and the x-axis denoting the number of iterations.

The convergence behavior varies notably across the hybrid configurations. The SVTS model (SVC optimized by TSOA) exhibits a steady, linear improvement in accuracy, reflecting a stable convergence pattern. In

contrast, the SVCG model (SVC optimized by CGO) demonstrates a less consistent trajectory, with noticeable fluctuations in accuracy, though an overall upward trend is still evident.

Similarly, the ETTS model (ETC optimized by TSOA) shows a smooth and consistent increase in accuracy, indicating robust convergence characteristics. The ETCG model (ETC optimized by CGO) achieves a sharper rise in accuracy, ultimately reaching a highly competitive performance level.

Among all models, ETTS achieved the highest final accuracy of 0.84, showcasing the effectiveness of the TSOA optimizer with the ETC classifier. Conversely, SVCG attained the lowest peak accuracy of approximately 0.77, suggesting less stable convergence when SVC is paired with CGO.

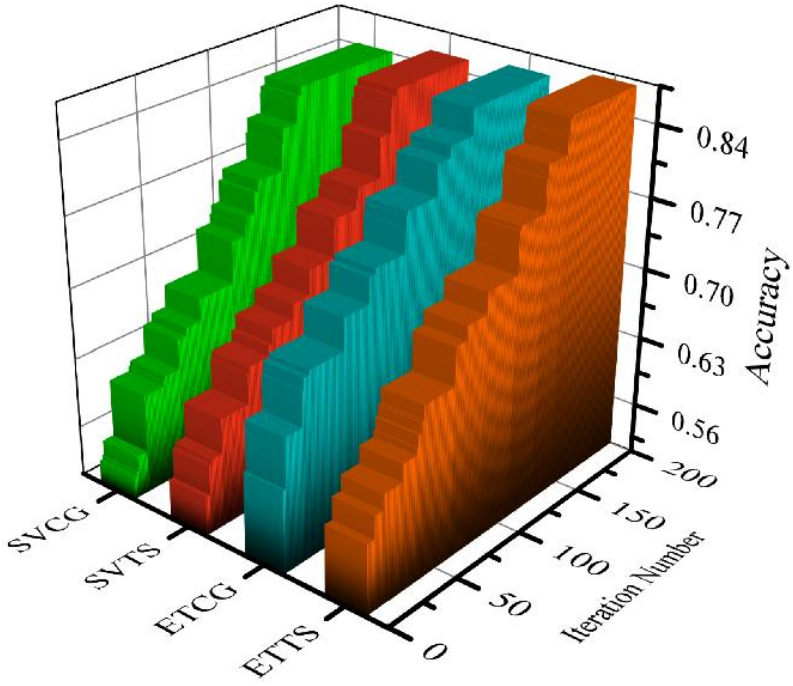


Figure 3: The convergence curve of the four presented hybrid models

Table 4 presents the performance metrics—Accuracy, Precision, Recall, and F1 Score—for both the training and testing phases of the base classifiers (ETC and SVC) and their corresponding hybrid variants (ETTS, ETCG, SVTS, and SVCG). Additionally, Figure 4 complements these results with 3D bar plots that provide a visual representation of the metric distributions for each model, highlighting comparative strengths in both learning and generalization capabilities.

Comparing the base model ETC with its hybrids, ETTS and ETCG, it is evident that both optimized variants consistently outperform the base model in both training and testing phases. For example, in the training stage, ETTS achieved the highest accuracy (0.910), followed closely by ETCG (0.897), while ETC lagged at 0.881. Similar trends are observed across Precision, Recall, and F1 Score. These performance gains continue in the testing phase, where ETTS and ETCG maintained superior generalization, with accuracies of 0.778 and 0.770, respectively, compared to ETC's 0.750.

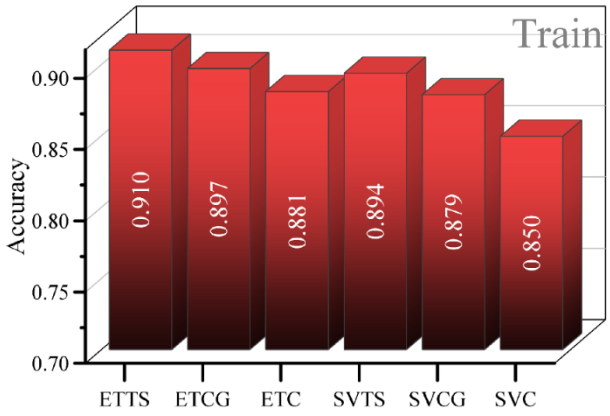
Likewise, for the SVC-based models, both SVTS and SVCG outperformed the baseline SVC during training. SVTS achieved an accuracy of 0.894, and SVCG recorded 0.879, compared to SVC's 0.850. Performance enhancements are also visible in Precision, Recall, and F1 Score. During testing, although the performance gap slightly narrows, SVTS still outpaces the base model with an accuracy of 0.760, whereas SVCG and SVC followed at 0.755 and 0.745, respectively.

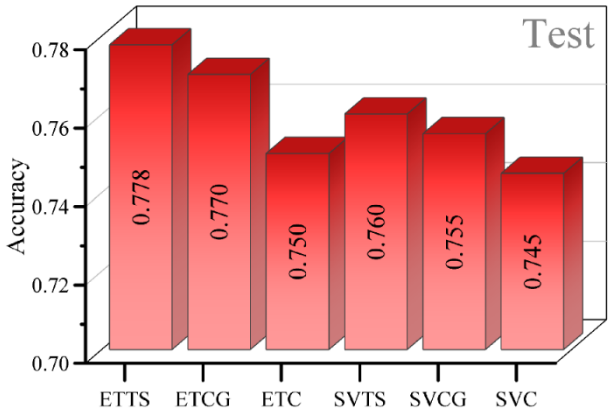
The visualized results in Figure 4 reinforces these findings. The 3D bar plots clearly illustrate the consistent superiority of hybrid models, particularly ETTS, across all evaluation metrics. The visual spacing between the bars reflects the degree of improvement, emphasizing how optimization algorithms—especially TSOA—enhance both model learning (training performance) and generalization (testing performance). The graphics also highlight that the ETTS model maintains the most balanced and highest-performing profile among all tested classifiers.

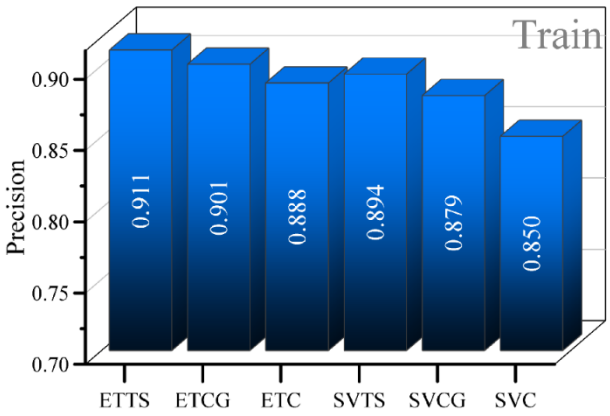
In summary, the combination of numerical evidence from Table 4 and graphical insights from Figure 4 confirms that hybrid models deliver significantly improved performance over their base classifiers. ETTS stands out as the most effective model, demonstrating the highest overall accuracy and stability across all metrics in both training and testing phases.

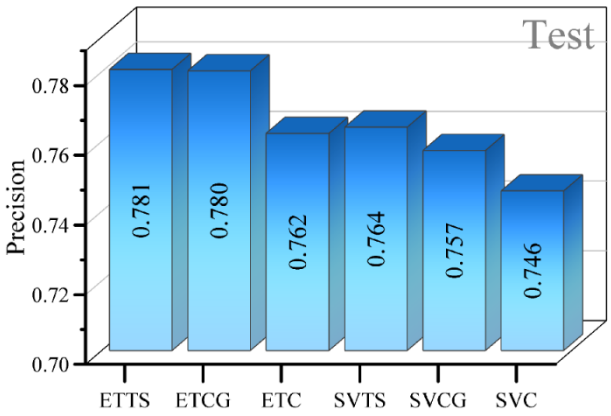
Table 4: ETC and SVC base models achieved results through the performance evaluators

Section	***Model***	**Metrics**			
		Accuracy	Precision	Recall	F1 Score
Training	ETTS	0.910	0.911	0.910	0.910
	ETCG	0.897	0.901	0.897	0.897
	ETC	0.881	0.888	0.881	0.880
	SVTS	0.894	0.894	0.894	0.894
	SVCG	0.879	0.879	0.879	0.879
	SVC	0.850	0.850	0.850	0.849
Testing	ETTS	0.778	0.781	0.778	0.778
	ETCG	0.770	0.780	0.770	0.769
	ETC	0.750	0.762	0.750	0.749
	SVTS	0.760	0.764	0.760	0.760
	SVCG	0.755	0.757	0.755	0.755
	SVC	0.745	0.746	0.745	0.745









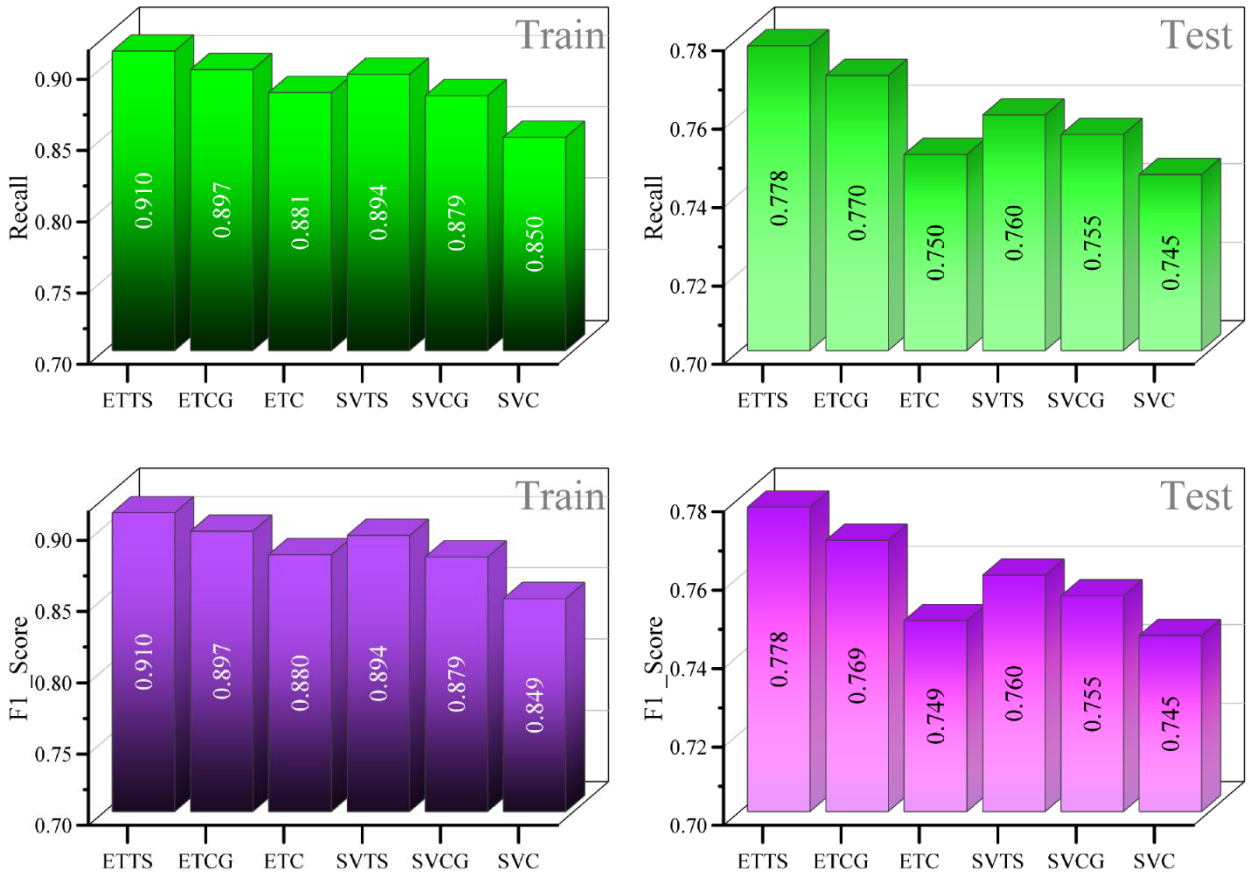


Figure 4: 3D bar plot for the performance of the models in train and test phases.

Table 4 outlines the performance metrics of base models and hybrid models. In a similar manner, Table 5 present the models' precision, Recall, and $F1\ score$ but in a more detailed breakdown of machine learning models that applied to water quality classification based on pH levels and categorized into Acidic, Basic, and Neutral conditions. The performance comparison of ETC with $ETTS$ reveals significant improvements across all pH conditions. For the Acidic condition, ETC displays an $F1\ score$ of 0.842, recall of 0.804, and precision of 0.883 , whereas $ETTS$ improves these metrics to 0.874 in precision, 0.868 in recall, and 0.871 in $F1\ score$. In the Basic condition, with a precision of 0.919, recall of 0.732, and $F1\ score$ of 0.815, ETC trails behind $ETTS$, which performs better with a precision of 0.890, recall of 0.807, and $F1\ score$ of 0.846. ETC reports an $F1\ score$ of 0.852, recall of 0.919, and precision of 0.794 for the Neutral condition. Whereas $ETTS$ achieves higher scores with 0.860 in precision, 0.901 in recall, and 0.880 in $F1\ score$. These numbers highlight the enhanced performance of $ETTS$, particularly in recall and $F1\ scores$, demonstrating the effectiveness of optimization. Both ETC and SVC show substantial improvements in precision, recall, and $F1\ scores$ when optimized with $TSOA$ and CGO, respectively. For instance, in the acidic condition, SVC achieves a precision of 0.800 while $SVTS$ outperforms SVC by improvement in precision to 0.865. The optimized models demonstrate superior capability in accurately classifying water quality, with $ETTS$ and $ETCG$ performing notably well in various metrics. Among all the models evaluated, the $ETTS$ model emerges as the best performer, achieving the highest overall accuracy in $pH-based$ water quality classification.

Table 5: Model performance in the three different conditions

Model	Condition	Metric			P-value
		precision	recall	f1-Score	
ETTS	Acidic	0.874	0.868	0.871	0.032
	Basic (alkaline)	0.890	0.807	0.846	0.027
	Neutral	0.860	0.901	0.880	0.018
ETCG	Acidic	0.887	0.834	0.860	0.04
	Basic (alkaline)	0.922	0.764	0.836	0.035
	Neutral	0.821	0.921	0.868	0.022
ETC	Acidic	0.883	0.804	0.842	0.045
	Basic (alkaline)	0.919	0.732	0.815	0.039

	Neutral	0.794	0.919	0.852	0.025
SVTS	Acidic	0.865	0.841	0.853	0.048
	Basic (alkaline)	0.841	0.811	0.826	0.041
	Neutral	0.852	0.883	0.867	0.029
SVCG	Acidic	0.840	0.825	0.832	0.052
	Basic (alkaline)	0.827	0.804	0.815	0.047
	Neutral	0.849	0.872	0.860	0.031
SVC	Acidic	0.800	0.801	0.801	0.059
	Basic (alkaline)	0.814	0.764	0.788	0.053
	Neutral	0.833	0.855	0.844	0.010

Figure 5 depicts a line plot illustrating the numerical differences in how well different machine learning models perform when used to classify water quality based on pH. This figure's main purpose is to compare various models' efficaciousness visually. Particularly focusing on the performance improvements achieved by incorporating sophisticated optimization algorithms. ETC and its hybrid version, $ETTS$, show distinct differences. ETC correctly predicts 558, 348, and 205 samples in neutral, acidic, and alkaline groups. While $ETTS$ improves upon this with a predicted value of 547, 376, and 226 samples in neutral, acidic, and alkaline, indicating an enhancement in accuracy. This improvement is quantified as a percentage difference in the accuracy of the models, with $ETTS$, in general, showing lower percentage differences compared to ETC, highlighting its enhanced predictive capability.

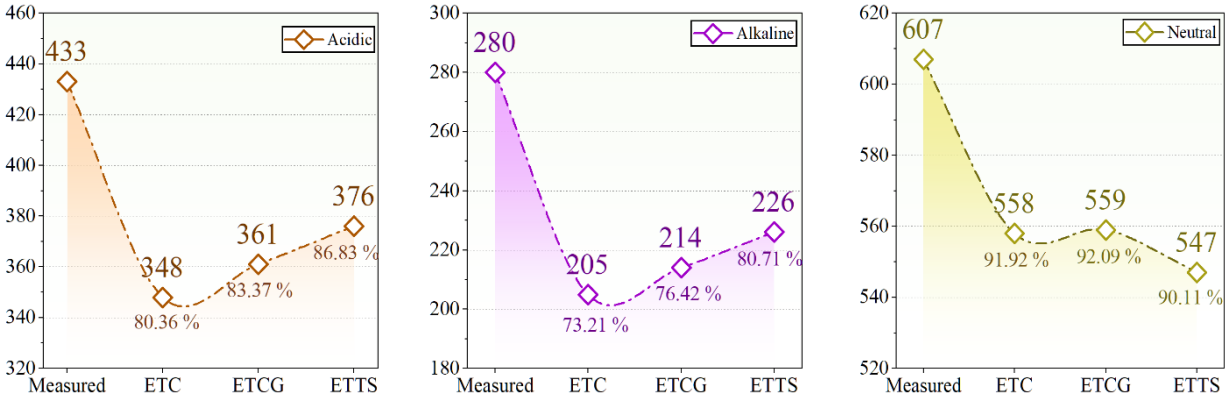


Figure 5: Line plot representing the number of correct predictions by ETC-based models

A comprehensive evaluation of each model's accuracy can be done thanks to the confusion matrix, which is depicted in Figure 6 and compares actual and predicted classifications. An illustration of the confusion matrix created by different machine-learning models for determining the pH-level-*based* classification of water quality is shown in Figure 6. Each model's accuracy can be thoroughly evaluated thanks to the confusion matrix, which displays actual versus predicted classifications. ETC predicts acidic samples with 348 correct, three misclassified as alkaline, and 82 as neutral. For alkaline samples, it predicts 205 samples correctly, with 12 samples misclassified as acidic and 63 samples as neutral. Neutral samples are predicted, with 558 samples correctly, 34 as acidic, and 15 as alkaline. When optimized using the Transit Search Optimization Algorithm, the hybrid model ($ETTS$) shows improved performance. $ETTS$ predicts acidic samples with 376 correct, seven misclassified as alkaline, and 50 as neutral. For alkaline samples, $ETTS$ predicts 226 correctly, with 15 misclassified as acidic and 39 as neutral. Neutral samples are predicted with 547 correctly, 39 as acidic, and 21 as alkaline. Comparatively, the $ETTS$ model outperforms its base model ETC, especially in predicting neutral samples with significantly higher accuracy. In acidic classification, $ETTS$ shows slight improvement with fewer misclassifications. For alkaline predictions, both models show comparable performance, though $ETTS$ has a marginally better accuracy. Among all models, the best performance is observed in the $ETTS$ model, indicating its superior capability in accurate $pH-based$ water quality classification.

	Acidic	Alkaline	Neutral
Acidic	376	7	50
Aalkaline	15	226	39
Neutral	39	21	547

ETTS

	Acidic	Alkaline	Neutral
Acidic	361	4	68
Aalkaline	12	214	54
Neutral	34	14	559

ETCG

	Acidic	Alkaline	Neutral
Acidic	348	3	82
Aalkaline	12	205	63
Neutral	34	15	558

ETC

Figure 6: Confusion matrix for the accuracy of each model.

To evaluate the classification performance of the models in predicting pH-based water quality, the Receiver Operating Characteristic (ROC) curves in Figure 7 are analyzed. These curves illustrate the trade-off between the true positive rate and the false positive rate at various threshold settings, providing a visual assessment of each model's diagnostic ability.

The micro-average ROC curve (green dashed line) aggregates the contributions of all classes, treating each prediction equally. It reflects the classifier's overall ability across all samples. The curve's steep initial rise indicates strong overall performance, with high sensitivity achieved at low false positive rates.

The macro-average ROC curve (red dashed line) calculates the average performance across classes by assigning equal weight to each one, regardless of class imbalance. It provides a balanced view of performance and shows a smoother increase in true positive rate compared to the micro-average.

Performance across specific pH categories is also shown:

- The acidic class (brown line) demonstrates moderate sensitivity at the outset, improving with higher false positive rates.
- The basic (alkaline) class (cyan line) exhibits the most favorable curve, with a sharp ascent indicating excellent classification performance at low false positive rates.
- The neutral class (purple line) shows a more gradual increase, reflecting a balanced but less pronounced trade-off between true and false positives.

Overall, the cyan curve representing basic pH conditions shows the highest classification accuracy, while the green micro-average curve confirms the robustness of the models in handling all classes collectively.

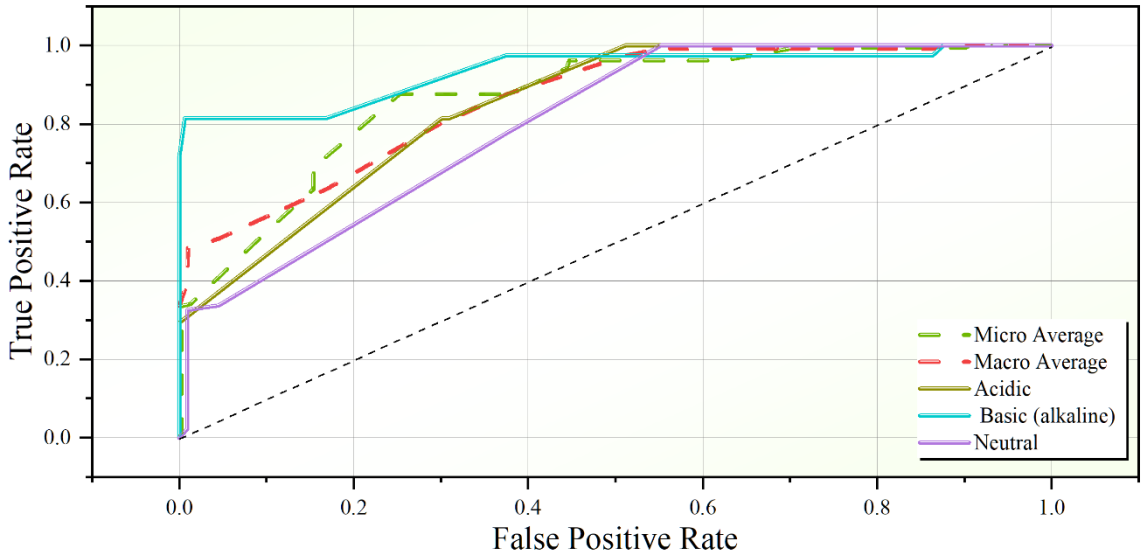


Figure 7: The ROC curves for the performance of the most efficient hybrid models

- **Wilcoxon test**

Figure 8 presents a radar plot of the Wilcoxon test statistics for all single and hybrid models: SVC, SVTS, SVCG, ETC, ETTS, and ETCG. The plotted values reflect the Wilcoxon test statistic for each model when compared pairwise, quantifying relative performance in terms of statistical ranking.

From the figure:

- SVC records the highest Wilcoxon statistic (13,521), indicating that its performance significantly differs—statistically outperforming or underperforming—relative to others.
- ETTS also scores high (12,648.5), suggesting a strong and consistent performance validated by statistical evidence.
- In contrast, SVTS and SVCG have lower statistics (9313 and 10,945.5, respectively), pointing to less statistical dominance or more variability across comparisons.
- ETCG and ETC show intermediate values (7725 and 10,063.5), reflecting moderate performance consistency.

The shaded blue region visually represents the distribution and spreads of the Wilcoxon test statistics across all models. A wider area suggests higher variability in model ranks, while more compact regions suggest more stability.

Overall, the Wilcoxon analysis complements accuracy-based evaluation by statistically confirming the comparative significance of the observed model performance differences.

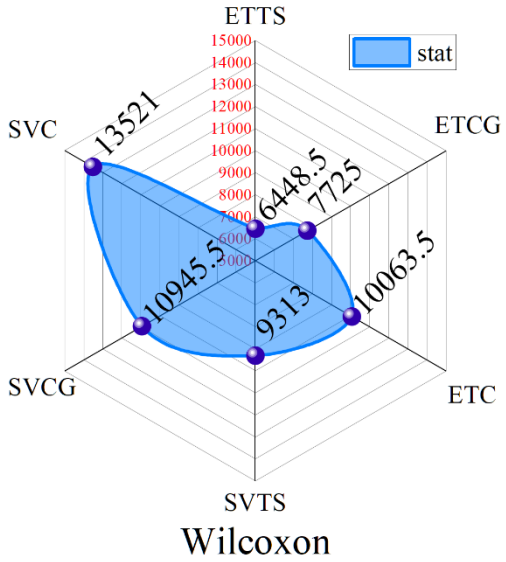


Figure 8: The results of Wilcoxon test for models' performance.

5 Discussion

5.1 Limitations of the study

While the proposed hybrid models (ETTS, ETCG, SVTS, and SVCG) demonstrated superior classification performance over their baseline counterparts, the study presents several limitations that warrant attention. First, the dataset used for model training and evaluation comprises only 1,320 daily records, which may limit the generalizability of the models across diverse geographical regions or seasonal variations. A larger and more heterogeneous dataset could improve robustness and reduce the risk of overfitting. Secondly, the models focus solely on pH as the output classification parameter, potentially neglecting the complex interactions of other water quality indicators (e.g., turbidity, nitrate levels) that may jointly influence classification outcomes.

5.2 Potential future studies

Building upon the promising results of this study, future research can explore several enhancements. One key direction is the expansion of the dataset, both temporally and spatially, to include diverse water bodies, seasonal dynamics, and additional environmental indicators. This would allow for the training of more generalizable models applicable to broader real-world conditions. Additionally, the integration of deep learning architectures—such as recurrent neural networks (RNNs) or convolutional neural networks (CNNs)—can be investigated for their potential to capture temporal or spatial correlations in water quality trends. Furthermore, an ensemble framework combining multiple hybrid models could be tested using voting or stacking strategies to further improve classification performance.

5.3 Practical implications of the study

The findings of this study highlight the practical viability of hybrid machine learning and optimization frameworks in environmental monitoring applications. By accurately classifying water quality based on pH levels, the proposed models can assist water resource managers, environmental agencies, and public health officials in making informed decisions regarding water treatment and ecosystem preservation. The enhanced predictive accuracy of the hybrid models ensures timely identification of acidic or alkaline deviations, which are critical for preventing metal toxicity, preserving aquatic biodiversity, and maintaining water usability for irrigation and drinking purposes. Moreover, the lightweight nature of the models (especially ETC and SVC) makes them suitable for deployment in embedded or real-time monitoring systems, offering

scalable solutions for smart water quality surveillance in both urban and rural settings.

5.4 Comparison between the results of present study and previous works

Table 6 presents a comparative analysis between the proposed hybrid model (ETC+TSOA) from the present study and several existing state-of-the-art methods in the domain of water quality classification. The comparison is based on classification accuracy, which is a key performance metric. Among the referenced studies, Putra et al. [17] achieved the highest accuracy (0.9828) using a Random Forest Regressor (RFR), followed closely by Idroes et al. [15] with a CATBoost model (0.9781). Sasmita et al. [16] employed a K-Nearest Neighbors (KNN) classifier and reported an accuracy of 0.9067. In contrast, the present study's ETC+TSOA model attained an accuracy of 0.91, outperforming the KNN-based model and demonstrating competitive results relative to more complex ensemble methods.

While the accuracy of the ETC+TSOA model is slightly lower than that of RFR and CATBoost, it is important to note that the proposed model leverages advanced metaheuristic optimization to enhance model performance while maintaining a balance between interpretability, computational efficiency, and generalization capability. This underscores the value of hybrid machine learning and optimization approaches, especially in resource-constrained or real-time environmental monitoring contexts.

Table 6: The Comparison between the results of present study and previous works.

Article	Reference	Model	Metrics
			Accuracy
Idroes et al.	[15]	CATBoost	0.9781
Sasmita et al.	[16]	KNN	0.9067
Putra et al.	[17]	RFR	0.9828
Present study	**-**	**ETC+TSOA**	**0.91**

6 Conclusion

Water quality is a very important aspect in which environmental health and safety can be ensured. For understanding aquatic ecosystems for the purpose of monitoring and management, proper classification of water quality is required, mainly based on their pH levels. This research article applied various methods of artificial intelligence and optimization algorithms for the categorization of the quality of water based on pH levels, hence providing a robust framework for environmental monitoring. In this research, the dataset used contains 1320 records in total; each record has information on the following input parameters: Date, Salinity, Dissolved Oxygen, secchi Depth, Water Depth, Water Temperature, and Air Temperature. The output parameter in this analysis is pH, or the level of acidity, alkalinity, and neutrality indicative of water. These are daily records; hence, they provide a holistic view of how the respective environmental matters are changing from day to day.

In the presented study, SVC and ETC were used for water quality prediction by considering pH as one of the main influential parameters. In the present study, a more advanced class of optimizers in the form of the Transit Search Optimization Algorithm and Chaos Game Optimization were coupled with the svcand ETC to improve their corresponding predictive accuracies. The obtained results reflected that the hybrid models $ETTS$, $ETCG$, $SVTS$, and $SVCG$ outperformed their base model with a significant difference in performance.

Comparing $ETTS$, when all models are taken into consideration against the ETC base model, it improves Accuracy by 3.73%, with increased Precision by 2.49%, boosted Recall by 3.73%, and increased $F1\,Score$ by 3.87%. On the other hand, $ETCG$ outperforms ETC with improved Precision by 2.36%, increased Accuracy and Recall by 2.67%, and a better $F1\,Score$ by 2.67% also. For SVC models, $SVTS$ increased Accuracy and Recall by 2.01%, increased Precision by 2.41%, and also increased the $F1\,Score$ by 2.01% from the base SVC. Similarly, $SVCG$ also outperformed SVC, with increases of 1.34% in Accuracy and Recall, and it boosted Precision by 1.47%. $ETTS$ turned out to be the best improvement among all, with the highest scores on all metrics.

High capability of hybrid models to provide more reliable and accurate pH-based water quality prediction underlines the potential for such advanced techniques in environmental monitoring and management. These results demonstrate how combining machine learning with advanced optimization algorithms yields significantly higher predictive accuracy and reliability for pH-based water quality classification. The usefulness of hybrid models in these applications, due to their increased accuracy, makes them very handy tools in the prediction of water quality, therefore helping in water body management and conservation.

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Hybrid Machine Learning Framework for Type 2 Diabetes Prediction Using Metaheuristic Optimization Algorithms

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Keywords: diabetes, machine learning**,** gaussian process classification, henry gas solubility enhancement schemes (HGSO), and metaheuristic algorithms

The general basis of diabetes prediction using machine learning involves the application of algorithms that take an overall look at multiple features like BMI and glucose levels, age, genetic predispositions, and other conditions that may predict the likelihood of developing diabetes. The data-driven schemes, such as neural networks or DTs, find patterns in past data and use these to provide reliable predictions about future diabetes cases. These schemes keep learning and improving; they grow with new inputs. ML now helps in early detection by the use of large datasets, thus enabling early actions such as lifestyle changes or medical therapies. Finally, it enhances healthcare by providing individualized risk assessment and thus enables timely actions to diminish the burden of diabetes. In addition, the application of ML schemes, including Gaussian Process Classification-GPC, Linear Discriminant Analysis-LDA with Henry Gas Solubility Optimization-HGSO, Chaos Game Optimization-CGO, and Chef-Based Enhancement scheme-CBOA, has greatly benefited the process of prediction. These schemes were combined with optimizers, guided by the objective of this work, which deals with predicting the type of diabetes and the diagnosis of persons vulnerable to it. This was a strategic fusion aimed at creating new hybrid schemes with increased precision in prediction. Further analysis showed that the GPCB model was the best, with an impressive 0.981 during training. By contrast, the GPCG and GPHG schemes are relatively less accurate, with an accuracy of 0.963 and 0.946, respectively. These results justify the utility of the integrated approach, where advanced ML algorithms were able to generate predictive schemes superior in terms of accuracy and efficiency compared to the classical methods.

Povzetek: V članku je opisan sistem za napovedovanje sladkorne bolezni tipa 2 s pomočjo strojnega učenja. Algoritem GPCB združuje klasifikacijo Gaussovega procesa z metahevrističnimi optimizacijskimi algoritmi za kvalitetno diagnozo.

1 Introduction

Type 2 diabetes, another name for diabetes, is a long-term metabolic illness marked by elevated blood glucose levels because of either the pancreas's insufficient production of insulin or its inability to utilize insulin effectively [1]. Insulin is a hormone produced by the pancreas that regulates blood sugar levels by allowing the absorption of glucose into the cells to use it as energy [2]. Whenever the mechanism is disturbed, glucose builds up in the circulation and causes hyperglycemia [3]. Diabetes is sorted into 3 types: type I, type II, and gestational diabetes [4]. Type 1 diabetes, which is frequently diagnosed in childhood or adolescence, is caused by the immune system erroneously targeting and killing the insulin-generating beta cells in the pancreas [5]. This involves lifetime insulin treatment to control blood sugar levels. Type 2 diabetes, the most prevalent kind, usually develops in adulthood and is often associated with overweight, lack of exercise, and genetic risk [6], [7]. Type 2 diabetes develops when the body becomes resistant to or cannot produce sufficient insulin to meet its needs, thereby resulting in high blood sugar levels [8]. Gestational diabetes develops during pregnancy when fluctuations in hormones compromise insulin activity, increasing the risk of complications for both mother and child [9], [10]. Diabetes' persistent High blood sugar levels can cause a stream of issues affecting many organ systems [11]. These include cardiovascular disorders including strokes and heart attacks; nerve damage; diabetic neuropathy; kidney damage causing numbness, tingling (diabetic nephropathy), and discomfort; as well as eye disturbances that can cause blindness due to diabetic retinopathy, if not addressed [12], [13]. Diabetes also raises the risk of ulcers in feet and amputations owing to impaired circulation and damage to nerves [14].

Management includes frequent testing of blood glucose, proper nutrition, regular physical activity, and insulin therapy or medication when necessary. Other treatments for type 2 diabetes include weight loss and smoking cessation. People with diabetes need training and support, as enabling them with skills for optimum self-

management reduces complications, reflecting a collaborative approach by all involved [15]: providers of healthcare, the patient, and family members [16], [17]. Type 2 is a complex metabolic condition that casts ripples in personal life since it has myriad implications for many facets [18], [19]. It presents physically as a constellation of symptoms that include chronic thirst and frequent urination, fatigue, and unexpected weight gain or loss [20], [21]. This chronic fight against blood sugar becoming normal turns out to be an everyday obsession with food intake, medication routines, and even social interactions [22]. Besides the physical discomforts, type 2 diabetes also has a great psychological and emotional impact. The constant monitoring required to manage the disease can lead to feelings of anxiety, stress, and depression. The fear of complications is huge, with every increase or decrease in glucose triggering a snowball effect of questions about what this could mean for long-term health and well-being.

Type 2 diabetes can negatively affect social relationships and interactions. Even going out for meals may become a maze of counting carbohydrates and administering insulin, while social events may become distressing in their demand to explain dietary restrictions or personally withdraw to check blood glucose levels [23]. The stigma associated with diabetes can also make people feel isolated or humiliated, disrupting interpersonal interactions [24]. Besides that, type 2 diabetes may lead to serious financial burdens. Pharmaceutical treatment, apparatus for blood glucose monitoring, and frequent medical consultations are not cheap, especially when insurance coverage is inadequate. Further, loss of working days due to poor health or visiting doctors may affect earnings and professional development [25]. Notwithstanding such constraints, persons with type 2 diabetes often show remarkable resilience and resourcefulness [26]. Most learn to manage the complexity of their disease through education, proactive self-management, and support networks and feel empowered by taking responsibility for their health. However, the pervasive nature of type 2 diabetes ensures its impacts are felt at all levels of life, making comprehensive approaches to prevention, treatment, and care of utmost importance.

Machine learning algorithms can predict the risk a person has for diabetes and even define which type of diabetes the person is most probable to get, considering his or her medical history, life style habits, biomarkers, and genetic trends. These algorithms are trained on large datasets consisting of data from diabetic and non-diabetic patients through a method called supervised learning. The computers learn to find, through patterns and links in data, small signs and risk factors associated with different types of diabetes [27]. For example, ML schemes for the diagnosis of type 2 diabetes consider age, BMI, family medical history of diabetes, cholesterol levels, blood pressure, and glucose tolerance. These combined indicators may, therefore, enable the model to project the likelihood of a person developing type 2 diabetes over a specific period [28]. Other ML methods, including DT, LR, and SVM, might also classify individuals into types of diabetes based on sets of different variables. This will enable individual risk assessments and prevention methods based on an individual profile, and in time, will allow healthcare professionals to offer more personalized and effective preventative treatment [29].

1.1 Objectives

This article proposes developing a scheme for diagnosing types of diabetes and predicting the likelihood of a person being affected with it. In order to solve this issue, the use of ML schemes including LDA and GPC is chosen, along with 3 optimizers: CGO, HGSO, and CBOA. The integration of these optimizers with the schemes leads to some new hybrid model generation, which is supposed to give better performance in the prediction process. Further, these newly designed hybrid schemes are evaluated for their performances using different plots and tables. It is expected that through their dense analysis, information about the most effective performance of the different schemes can be extracted, along with the potential deficit in functionality among them. Such an inclusive strategy will provide thorough knowledge about various schemes' strengths and flaws that help in formulating approaches related to the diagnosis and prediction of diabetes.

Gaussian Process Classification (GPC) and Linear Discriminant Analysis (LDA) were picked owing to their complimentary capabilities in modeling classification challenges. GPC is a non-parametric, probabilistic model that captures complicated, nonlinear interactions and offers uncertainty estimates, making it suited for the nuanced and high-risk nature of diabetes prediction. Conversely, LDA is a basic yet powerful linear classifier that performs well when class distributions are nearly Gaussian. Its interpretability and minimal computing cost make it suitable for baseline comparison. LDA is good for efficiency and understanding, while GPC is good for making strong, adaptable models of complicated health data patterns. Together, they make a balanced framework.

2 Material and methods

2.1 Data collection

Prior to model training, the dataset underwent several preprocessing procedures to enhance data quality and model performance. Missing values were addressed using mean imputation for numerical features. Outliers were detected and mitigated using z-score normalization. All continuous features were standardized to zero mean and unit variance. Categorical variables, if any, were encoded using one-hot encoding. Feature selection was conducted using mutual information to retain only the most relevant predictors. The final dataset was randomly shuffled and split into training and testing sets using an 70:30ratio to ensure unbiased model evaluation. Fig. 1 displays the far-reaching consequences of diabetes on a person's life, spanning blood pressure to pregnancy, as it affects an

individual's well-being and lifestyle in general. This study tries to make meaning out of the interaction of diabetes with these major determinants, therefore, basically determining the trend of the illness.

- High blood pressure worsens diabetes complications by essentially destroying blood vessels and organs. High blood pressure and atherosclerosis accelerate the narrowing of arteries, which limits blood flow, thereby worsening the common diabetes consequences of heart disease, stroke, and kidney failure. Hypertension further increases the risk for diabetic retinopathy, which can cause visual impairment or even total blindness. It also leads to peripheral artery disease, which raises the chances of foot ulcers and amputations in diabetic patients. Good management of blood pressure through lifestyle modifications, medication, and regular checks is of utmost importance in effective management and reduction of adverse effects of diabetes on general health. Pregnancy complicates the care of diabetes because of fluctuating hormonal changes and increased insulin resistance.
- Gestational diabetes may be developed during pregnancy, increasing the risk for complications in both mother and child, including macrosomia, preeclampsia, and anomalies at birth. Women with previous diabetes have difficulties managing blood sugar levels, again increasing risks for adverse outcomes such as preterm birth and cesarean section delivery. Close monitoring, dietary modification, and medication may be necessary to achieve appropriate risk reduction and optimal health for both mother and fetus. Such cooperation between obstetricians, endocrinologists, and diabetes educators forms the very foundation for the best pregnancy outcomes among women with diabetes.

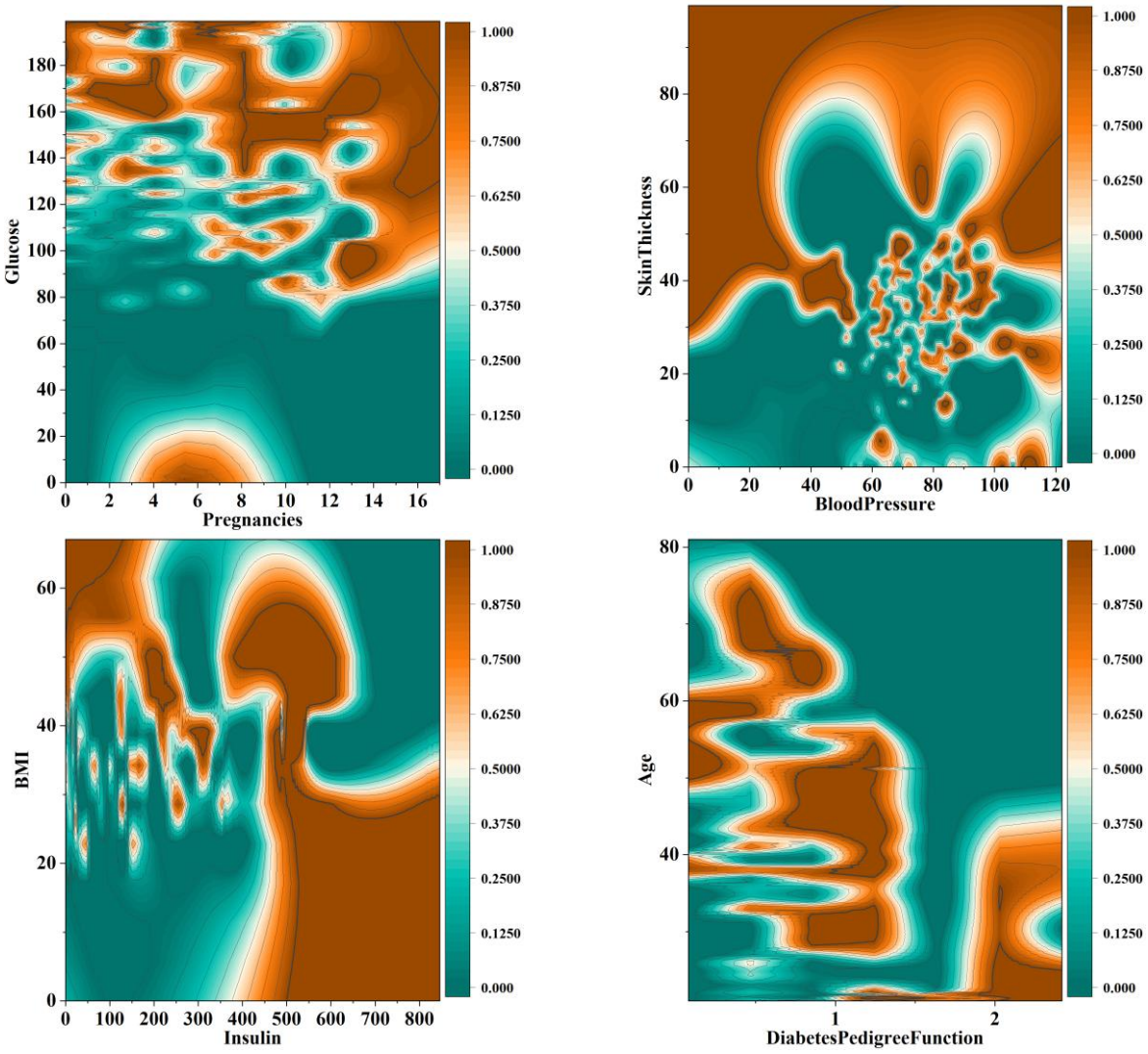


Figure 1: The plot illustrating the Contour - color fill between the input and output

2.2 Linear discriminant analysis (LDA)

Linear Discriminant Analysis (LDA) is a statistical approach used to separate two or more classes by identifying a linear combination of characteristics that best differentiates them. It assumes that the different classes create data based on Gaussian distributions with the same covariance matrix. LDA is computationally efficient, interpretable, and particularly successful when the relationship between features and labels is nearly linear, making it suited for baseline comparison in medical classification problems like diabetes prediction.

LDA assumes that the 2 categories' matrices of covariance are similar [30], and one of the 2 categories has a greater average than the other, as seized $\mu_1 < \mu_2$. One of these examples is the one provided for $x \in R$ classes:

$$\Sigma_1 = \Sigma_2 = \Sigma. \tag{1}$$

$$\begin{aligned} &\frac{1}{\sqrt{(2\pi)^d|\Sigma|}} exp\left(-\frac{(x-\mu_1)^T\Sigma^{-1}(x-\mu_1)}{2}\right)\pi_1 \\ &= \frac{1}{\sqrt{(2\pi)^d|\Sigma|}} exp\left(-\frac{(x-\mu_2)^T\Sigma^{-1}(x-\mu_2)}{2}\right)\pi_2, \\ &\Rightarrow exp\left(-\frac{(x-\mu_1)^T\Sigma^{-1}(x-\mu_1)}{2}\right)\pi_1 \\ &= exp\left(-\frac{(x-\mu_2)^T\Sigma^{-1}(x-\mu_2)}{2}\right)\pi_2, \\ &\overset{(a)}{\Rightarrow} -\frac{1}{2}(x-\mu_1)^T\Sigma^{-1}(x-\mu_1) + \ln(\pi_1) \\ &= -\frac{1}{2}(x-\mu_2)^T\Sigma^{-1}(x-\mu_2) + \ln(\pi_2) \end{aligned} \tag{2}$$

The simple logarithm of the equation's sides is found by (a). The equation may be written as:

$$\begin{aligned} &(x-\mu_1)^T\Sigma^{-1}(x-\mu_1) = (x^T - \\ &\mu_1^T)\Sigma^{-1}(x-\mu_1) = x^T\Sigma^{-1}x - x^T\Sigma^{-1}\mu_1 - \\ &\mu_1^T\Sigma^{-1}x + \mu_1^T\Sigma^{-1}\mu_1 \overset{(a)}{=} x^T\Sigma^{-1}x + \mu_1^T\Sigma^{-1}\mu_1 - \\ &2\mu_1^T\Sigma^{-1}x \end{aligned} \tag{3}$$

Where (a) is because $x^T\Sigma^{-1}\mu_1 = x^T\Sigma^{-1}x$ since Σ^{-1} is balanced and $\Sigma^{-T} = \Sigma^{-1}$. As a result, it is observed:

$$\begin{aligned} &-\frac{1}{2}x^T\Sigma^{-1}x - \frac{1}{2}\mu_1^T\Sigma^{-1}\mu_1 + \mu_1^T\Sigma^{-1}x + \ln(\pi_1) \\ &= \frac{1}{2}x^T\Sigma^{-1}x - \frac{1}{2}\mu_2^T\Sigma^{-1}\mu_2 + \mu_2^T\Sigma^{-1}x + \ln(\pi_2) \end{aligned} \tag{4}$$

As an outcome of multiplying both sides of the equation by 2, the expression that follows is obtained:

$$\begin{aligned} &2(\Sigma^{-1}(\mu_2-\mu_1))^T x + (\mu_1-\mu_2)^T\Sigma^{-1}(\mu_1-\mu_2) \\ &+ 2\ln\left(\frac{\pi_2}{\pi_1}\right) = 0 \end{aligned} \tag{5}$$

The equation of a line may be represented as $a^T x + b = 0$. T As a result, if the Gaussian distributions of the 2 classes are considered, and the covariance matrices are considered to be equal, a line displays the categorization choice border. This approach is called LDA because the choice border between the 2 classes is linear. The expressions were relocated to the correct side, which related to the second class, to create Eq. (5). Therefore, if used $\delta(x)$: $\mathbb{R}^d \to \mathbb{R}$ as the left-hand side calculation (function) in Eq. (6).

$$(x) := 2\left(\Sigma^{-1}(\mu_2-\mu_1)\right)^T x \tag{6}$$

$$+(\mu_1-\mu_2)^T\Sigma^{-1}(\mu_1-\mu_2)) + 2\ln\left(\frac{\pi_2}{\pi_1}\right)$$

An instance x's intended class is:

$$\hat{C}(x) = \begin{cases} 1, if\ (x) < 0, \\ 2, if\ \delta(x) > 0. \end{cases} \tag{7}$$

When both categories have identical priors, $\pi_1 = \pi_2$, Eq. (5) takes a particular form:

$$\begin{aligned} &2\left(\Sigma^{-1}(\mu_2-\mu_1)\right)^T x + (\mu_1-\mu_2)^T\Sigma^{-1}(\mu_1-\mu_2) \\ &= 0, \end{aligned} \tag{8}$$

Whose statement on the left can be interpreted as $\delta(x)$ in Eq. (7).

2.3 Gaussian process classification (GPC)

Gaussian Process Classification (GPC) puts a Gaussian process prior over a latent function to predict the chance of being in a certain class. This lets GPC capture nonlinear patterns in big datasets in a flexible way and measure how uncertain predictions are, which is very important for medical diagnostics. GPC is better for risk-sensitive predictions like figuring out how likely someone is to have diabetes since it changes its complexity dependent on the input. This is different from fixed parametric models.

Given a set of N training input points, in typical classification using Gaussian methods, procedure $X = [x_1, \ldots, x_N]^T$ and their associated class designations $Y = [Y_1, \ldots, Y_N]^T$, one would like to forecast the class participation percentage of a fresh test point $x_\times$. This may be accomplished by utilizing a latent function f, which is then mapped onto the [0; 1] interval utilizing the probit operator. For binary classification, use the notion that y belongs to {0,1}, where 1 displays the positive class and 0 displays the negative. Therefore, the likelihood of class membership $p(y = 1|x)$ might be expressed as Φ(f(x)), where Φ(.) is the probit purpose. Gaussian procedure classification is then performed by applying a GP prior to the latent function of $f(x)$. A GP [31] is a random procedure completely described by a mean function $m(x) = \mathbb{E}[f(x)]$ and a positive definite covariance method $\mathbb{k}(x; \acute{x}) = \mathbb{v}[f(x); f(\acute{x})]$. To project an additional test point $x_\times$, first calculate the range of the related latent variable $f_\times$.

$$p(f_\times|x_\times, X, y) = \int p(f_\times|x_\times, X, f)\, p(f|X, y)df \tag{9}$$

Where $f = [f_1, \ldots, f_N]^T$, and then using this distribution, calculate the class participation distribution:

$$\begin{aligned} &p(y_\times = 1|x_\times, X, y) \\ &= \int \Phi(f_\times)\, p(f_\times|x_\times, X, y)df_\times \end{aligned} \tag{10}$$

2.4 HGSO

The following subsection describes the motivation for HGSO, which depends on the act of Henry's law.

2.4.1 Henry's Law

In 1803, William Henry created Henry's Law, a gas law [32]. Henry's law reads as follows: "At a temperature that remains constant, the amount of a given gas that dissolves

in a given type and volume of liquid is inversely related to the partial pressure that exists for that gas in equilibrium with that liquid." Consequently, Henry's law is greatly dependent on temperature [33] and displays that a gas's solubility (Sg) is directly proportional to its relative pressure (Pg), as represented in the subsequent equation:

$$S_g = H \times P_g \tag{11}$$

Where H is Henry's stable, which is particular to the given gas-solvent mixture at a certain temperature, and P_g is the gas's relative pressure.

$$\frac{dlnH}{l(1/T)} = \frac{-\nabla sol^E}{R} \tag{12}$$

Furthermore, the impact of temperature dependency on Henry's law variables has to be addressed. The Van't Hoff equation describes how Henry's law constants vary when a system's temperature varies:

$$H(T) = \exp(B/T) \times A \tag{13}$$

Where H is an expression of 2 parameters, A as well as B, which are the 2 factors that determine H's T dependency. In addition, one can generate a function based on H at the standard temperature $T = 298.15K$.

$$H(T) = H^{\theta} \times exp\left(\frac{-\nabla sol^E}{R}\left(1/T - 1/T^{\theta}\right)\right) \tag{14}$$

The Van't Hoff formula applies if $-\nabla sol^E$ is a stable, hence Eq. (14) may be rewritten as follows:

$$H(T) = exp\left(-c \times \left(1/T - 1/T^{\theta}\right) \times H^{\theta}\right) \tag{15}$$

2.4.2 HGSO mathematical scheme

This part describes the mathematical formulas for the suggested HGSO method. The mathematical procedures are outlined below:

Step 1: Initialization process.

The count of gases (population size N) and the placements of gases have been set up using the subsequent equation:

$$X_i(t+1) = X_{min} + r \times (X_{max} - X_{min}) \tag{16}$$

where t is the repetition time, X_{min} and X_{max} are the issue bounds, r is a random number between 0 and 1, and X_i is the location of the ith gas in population N. The below equation is used to establish the count of gasses i, Henry's constant of type j ($H_j(t)$) partial pressure $P_{i,j}$ of gas i in cluster j, and $-\nabla sol^E/R$steady value of type j (C_j).

$$H_j(t) = l_1 \times rand(0,1), P_{i,j} = l_2 \times rand\ (0,1), C_j = l_3 \times rand(0,1) \tag{17}$$

where l_1, l_2, and l_3 are designated as constants with corresponding amounts of $5E-02$, 100, and $1E-02$.

Step 2: Clustering.

In proportion to the count of gas types, the entire number of agents is split into equal clusters. Every cluster has the same Henry's constant measurement (H_j) since they all contain the same gases.

Step 3: Evaluation.

The gas having the largest equilibrium state among the others of its sort is identified by analyzing each cluster j. The optimal gas for the entire colony is then determined by rating the gasses.

Step 4: Update Henry's coefficient.

Eq. (18), which updates Henry's factor, is as follows:

$$H_j(t+1) = H_j(t) \times exp\left(-C_j \times \left(\frac{1}{T(t)} - \frac{1}{T^{\theta}}\right)\right), T(t) = \exp(-t/iter) \tag{18}$$

T displays the temperature, T^{θ} displays a constant equal to 298.15, iter is the overall count of cycles, and H_j is Henry's factor for cluster j in this equation.

Step 5: Update solubility.

The following formula is used to modify the solubility:

$$S_{i,j}(t) = K \times H_j(t+1) \times P_{i,j}(t) \tag{19}$$

$S_{i,j}$ is the soluble content of gas i in cluster j, $P_{i,j}$ is the amount of partial pressure on gas i in cluster j, and K is a value that is constant.

Step 6: Update position.

The position was revised below:

$$X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times \left(X_{i,best}(t) - X_{i,j}(t)\right) + F \times r \times \alpha \times \left(S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t)\right) \tag{20}$$

$$\gamma = \beta \times exp\left(-\frac{F_{best}(t)+\varepsilon}{F_{i,j}(t)+\varepsilon}\right), \varepsilon = 0.05$$

Where $X_{i,j}$ displays the location of gas i in cluster j, and r and t are the random constant and cycle time, respectively. The best gas in cluster j is indicated by X_{best}, while the best gas in the entire swarm is shown by $X_{i,best}$. In addition, γ displays gas $j's$ capacity to interact with other gases in cluster i, α displays the effect of other gases on gas i in cluster j and is equal to 1, and β is a constant. The fitness of gas i in cluster j is denoted by $F_{i,j}$, whereas F_{best} displays the fitness of the best gas in the overall system. F is the flag that modifies the direction of the search agent and gives variety ($\pm$). $X_{i,best}$and X_{best} are the 2 parameters that control the exploration and exploitation capabilities. Particularly, $X_{i,best}$ displays the best gas i in cluster j, whereasX_{best} displays the best gas in the whole swarm.

Step 7: Escape from local optimum.

The purpose of this phase is to leave the local optimum. The count of worst agents N_w can be chosen and ranked using the following equation:

$$N_w = N \times (rand(c_2 - c_1) + c_1), c_1 = 0.1\ and\ c_2 = 0.2 \tag{21}$$

The count of search agents is denoted by N.

Step 8: Update the position of the worst agents.

$$G_{(i,j)} = G_{\min(i,j)} + r \times \left(G_{\max(i,j)} - G_{\min(i,j)}\right) \tag{22}$$

In Eq. (22), $G_{(i,j)}$ displays gas i's position in cluster j, r is a random integer, and $G_{\min(i,j)}$ and $G_{\max(i,j)}$ represent the problem boundaries. The steps of the process are depicted in Fig. 2.

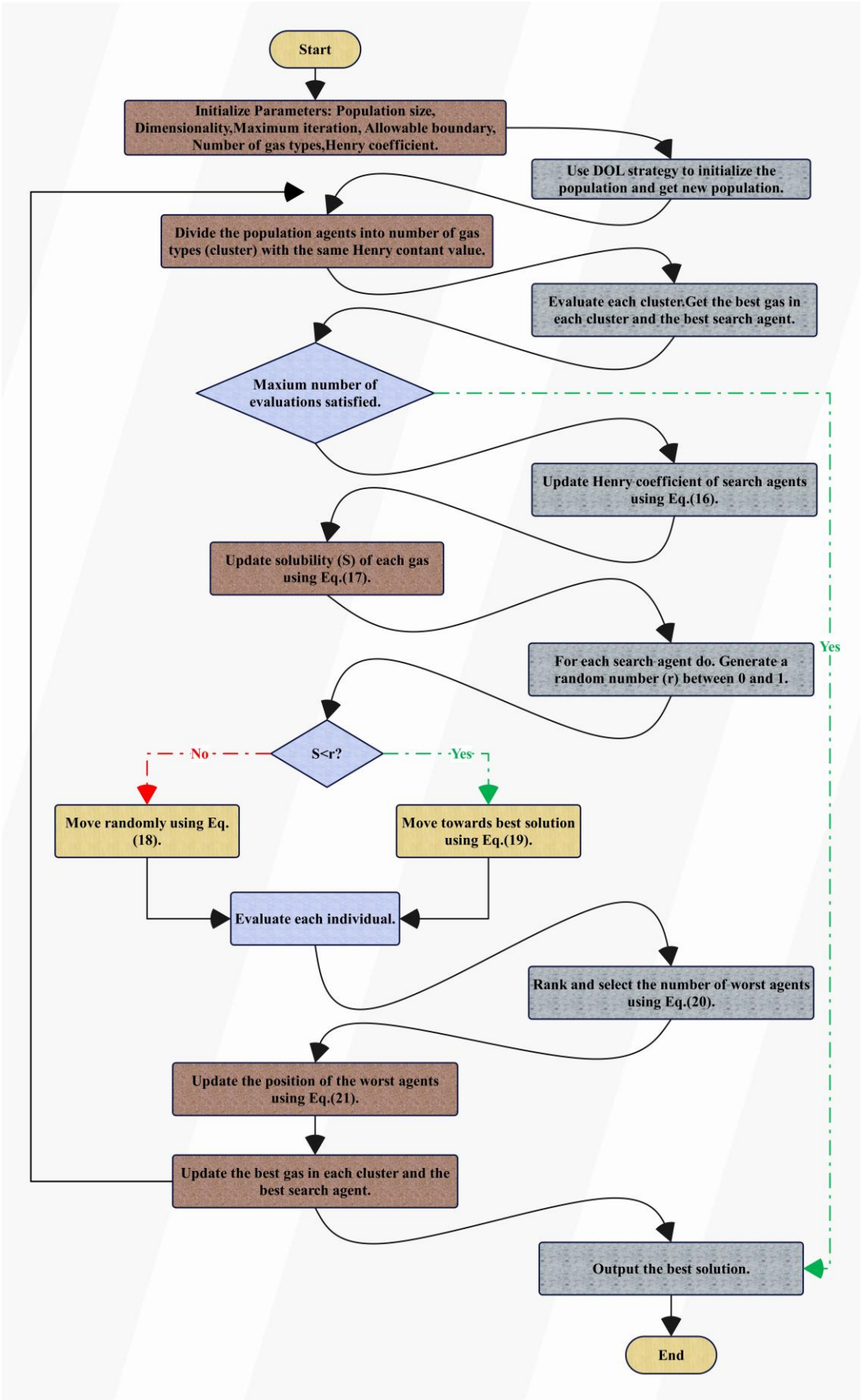


Figure 2: The flowchart of the HGS.

2.5 Chaos game optimization (CGO)

The reasons behind the groundbreaking metaheuristic algorithm known as CGO and its computational architecture are covered in this section.

2.5.1 Mathematical model

This section presents an optimization technique based on the ideas of chaos theory. The mathematical foundation of the CGO algorithm is developed based on the basic concepts of fractals and chaotic games. The CGO algorithm considers several solution candidates (X) that suggest certain able seeds within a Sierpinski triangle because many natural evolution algorithms keep an array of solutions that evolve through random modifications and selections. Each solution candidate (X_i) in this method contains a set of choice factors (x_i^j) that represent where the eligible seeds are located inside a Sierpinski triangle. The enhancement scheme uses the Sierpinski triangle to explore potential solutions. In the enhancement scheme, the Sierpinski triangle is used to look for possible solutions. The quantitative treatment of these aspects is given below:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^j & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^j & \dots & x_2^d \\ \vdots & \vdots & \dots & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \dots & x_i^j & \dots & x_i^d \\ \vdots & \vdots & \dots & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \dots & x_n^i & \dots & x_n^d \end{bmatrix}, \begin{cases} i = 1,2,..,n. \\ i = 1,2,\dots,d. \end{cases} \quad (23)$$

For each seed in the Sierpinski triangle (search area), the count of permissible seeds, or potential solutions, is n; and d is the seed's size. Random selection is used to determine where these appropriate seeds are initially placed in the search space.

$$x_i^j(0) = x_{min}^i + rand \cdot \left(x_{i,max}^j - x_{i,min}^j\right), \begin{cases} i = 1,2,\dots,n. \\ j = 1,2,\dots,d. \end{cases} \quad (24)$$

The beginning position of the eligible seeds is defined by x_i^j; $x_{i,max}^j$ as well as $x_{i,min}^j$ indicate the maximum and lowest permitted values for the ith solution candidate's jth choice variable; rand is a random integer within the range [0,1]. The way dynamical systems, often known as self-similar and self-organizing systems, behave, as was previously described, and display specific fundamental patterns serves as the foundation for the core ideas of chaos theory. The fundamental dynamical system patterns according to chaos theory are exhibited by eligible seeds, which are acquired beginning positions. It is possible to ascertain whether these seeds are suitable to function as fundamental patterns (self-similarity) for an optimization issue by employing potential solutions (X). The candidates for the solutions with the greatest and worst fitness values as well as the lowest and highest levels of eligibility are connected.

The basic idea of this mathematical model is to create the general shape of a Sierpinski triangle by producing several appropriate seeds inside the search area. In this way, fresh seeds are also produced via the Sierpinski triangle technique. An intermediate triangle with three seeds is created as follows for each appropriate seed in the search field X_i:

- Positioning of the previously identified Global Best (GB),
- The average group's location (MG_i),
- The ith resolution competitor (X_i) is the chosen seed.

Although the mean values of randomly chosen eligible seeds with an equal chance of integrating the currently regarded starting eligible seed (X_i) are reflected in the MG_i, the GB is the best solution candidate with the highest eligibility levels. Together with the identified eligible seed (X_i), the GB and MG_i create a Sierpinski triangle. In order to generate some more seeds that can be regarded as fresh eligible seeds for finishing the Sierpinski triangle, a temporary triangle is made inside the search area for each of the first eligible seeds, as was previously indicated. Four strategies are suggested to accomplish this aim. The ith permanent triangle (ith repetition) includes a Sierpinski triangle's three vertices [GB (green seed), MG_i (red seed), and X_i (blue seed)] in addition to the n appropriate seeds that were accessible in the previous cycle. This homemade triangle uses the chaotic game principle to produce fresh seeds using one die and three seeds. X_i is used to hold the first seed, GB for the second, and MG_i for the third. For the first seed, a die with three green and three red faces was utilized. Upon rolling the dice, the seed in the $X_i$is shifted to the MG_i (red face) or the GB (green face) based on the resulting color. This element is replicated using a random number generation method that generates just 2 values, 0 as well as 1, enabling the choice of red or green faces. When the green face is visible, the X_i seed advances in the direction of the GB; it moves toward the MG_i. Even if each green or red face has an equal chance of appearing in the game, the potential of getting two equivalent random integers for the GB and the MG_i is also taken into account. The direction of the X_i's seed advancement is a line segment that connects the GB with the MG_i. The flow of seeds within the search area must be restricted because of the chaotic game method; hence, this component is controlled by certain at-random factorials that were created:

$$Seed_i^1 = X_i + \alpha_i \times (\beta_i \times GB - \gamma_i \times MG_i), i = 1,2,\dots,n. \quad (25)$$

X_i displays the ith resolution candidate, GB denotes the global best discovered thus far, and MG_i displays the mean of a few selected, qualified seeds. While β_i and γ_i indicate a random integer between 0 and 1 to enable die rolling, α_i is a randomly generated factorial to reflect seed movement limitations. Three blue and three red-faced dice are used for the next seed (GB). Either the MG_i (red face) or the X_i (blue face) receives the seed in the GB, depending on the color that emerges from rolling the dice.

The model used in this section is the same as the original seed. If a blue face emerges, the seed travels to the X_i; if a red face appears, the seed goes to the MG_i. Another seed, like the first, can travel towards a location on the connecting lines between $X_i$and MG_i. This motion is restricted by randomly produced factorials.

$$Seed_1^2 = GB + \alpha_i \times (\beta_i \times X_i - \gamma_i \times MG_i), i = 1,2,\dots,n. \quad (26)$$

where each of the variables β_i and γ_i is a random value of 0 or 1 to simulate the option of rolling a die, and α_i is the randomly generated factorial for characterizing the mobility limitations of the seeds. The remaining requirements are the same as those listed for the initial seed. The third seed is employed to roll a die with green and blue faces, MG_i. The seed is directed toward either the X_i (blue face) or the GB (green face) depending on the color. An approach for generating random numbers is used to duplicate this element. It yields just 2 values, 0 and 1, so that users may select between the blue or green faces. Additionally, the lines connecting the X_i and GB can be followed by the seed. Some random factorials are also used to achieve this goal, such as:

$$Seed_1^3 = MG_i + \alpha_i \times (\beta_i \times X_i - \gamma_i \times GB), i = 1,2,\dots,n. \quad (27)$$

In order to generate the fourth seed, an additional method is employed to carry out the modification stage in the qualifying seeds' position updates within the search area. Changes in this seed's position are made depending on arbitrary adjustments made to the randomly chosen decision criteria. Eq. (28) depicts a schematic depiction of the specified procedure for the 4th seed; it has the following mathematical representation:

$$Seed_i^4 = X_i\left(x_i^k = x_i^k + R\right), \quad k = [1,2,\dots,d]. \quad (28)$$

Where k is an integer at random in the interval $[1,\ d]$ and R is a random number with uniform distribution in the region $[0, 1]$. Four formulations for αi, which controls the mobility limitations of the seeds, are provided in order to alter the exploration and exploitation rate of the CGO algorithm.

$$\alpha_i = \begin{cases} Rand \\ 2 \times Rand \\ (\delta \times Rand) + 1 \\ (\varepsilon \times Rand) + (\sim\varepsilon) \end{cases} \quad (29)$$

In this case, δ as well as ε are indeterminate numbers in the interval [0,1], and Rand is a randomly dispersed, equally distributed number in that interval. Given the self-similarity problems in the fractals, the eligibility of the new and existing seeds should be jointly assessed to decide if the additional seeds ought to be included in the search space's overall count of eligible seeds. The best new solution candidates are retained after being vetted; seeds with the lowest fitness values, or the lowest degrees of self-similarity, are removed. It is important to note that the mathematical method reduces the mathematical model's complexity by using substitution. Actually, the entire form of the Sierpinski triangle has been completed using all of the qualifying seeds found in the search region. To cope with the solution variables x_i^j breaching the boundaries of the factors, a mathematical flag is constructed. For the variables that violate the technique, a boundary change is ordered if the x_i^j is beyond the parameter's range. The most repetitions that can be done in which the optimization process takes place serves as the basis for the termination criterion.

2.6 Chef-Based Enhancement scheme (CBOA)

A metaheuristic method called CBOA was just introduced by [34]. The CBOA's mathematical representation and natural architecture are covered in this section.

2.6.1 Mathematical model of CBOA

Below is a presentation of the CBOA mathematical model using the situation from Section 2.1. First, the initialization stage of the algorithm is initiated, much like in other metaheuristics. There are 2 populations as a result of the CBOA: elite agents and candidate solutions. Therefore, as shown by Eq. (30), a matrix may be used to represent the CBOA members.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} x_{1,1} & \dots & x_{1,dim} \\ & \ddots & \\ x_{N,dim} & \dots & x_{N,dim} \end{bmatrix}_{N\times dim} \quad (30)$$

where N is the population size, dim is the issue length ($a \in [1, N], b \in [1, dim]$), X is the CBOA population matrix, and $x_{a,b}$ indicates the value of the bth problem parameter for the ath CBOA member. CBOA members' locations are established using Eq. (31):

$$x_{a,b} = LOW_b + rand \cdot (UP_b - LOW_b) \quad (31)$$

Where rand is an arbitrary number in the range of [0, 1], LOW_b and UP_b are the lower and upper limits of the bth problem factor, correspondingly. Each member's goal function may be determined and expressed as a vector according to Eq. (32):

$$Fit = \begin{bmatrix} FitxX_1 \\ \vdots \\ FitX_N \end{bmatrix}_{N\times 1} \quad (32)$$

Fit symbolizes the values of objective functions, whereas $FitX_a$ displays the value of a member. The objective function's value is used as the selection criteria for selecting the best candidate solution. The optimal member of the population and potential solution is the one that has the highest value for the objective function. It's time to complete the CBOA's processing steps after the algorithm has been launched. The CBOA is composed of two demographic groups: elite agents and candidate solutions. These two groups' update procedures are different. Its elements are changed at each cycle, and the values of the aim function are computed and evaluated. As a result, the best member is changed after each repetition. Upon comparing the values of the objective function, elite agents are selected from among the CBOA members with the highest values. The values of the goal function are used to sort the population matrix in decreasing order.

$$SX = \begin{bmatrix} SX_1 \\ \vdots \\ SX_{NC} \\ \vdots \\ SX_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} sx_{1,1} & & sx_{1,dim} \\ \vdots & & \vdots \\ sx_{NC,1} & & sx_{NC,dim} \\ sx_{NC+1,1} & \cdots & sx_{NC+1,dim} \\ \vdots & & \vdots \\ sx_{N,1} & & sx_{N,dim} \end{bmatrix}_{N\times dim} \quad (33)$$

$$SFit = \begin{bmatrix} SFitX_1 \\ \vdots \\ SFitX_{NC} \\ SFitX_{NC+1} \\ \vdots \\ SFitX_N \end{bmatrix}_{N\times 1} \quad (34)$$

Where NC is the count of chef instructors, SX denotes the sorted demographic matrix, and SFit displays the ascending objective function value vector. Following that, changes will be made in 2 steps for each group, from 1 to NC and $NC + 1\ to\ N$. NC has started to represent one-fifth of the entire population in the first group division. For instance, NC = 6 if there are 30 populations in the beginning. All cycles or the end of the epochs result in the availability of a single chef.

Step 1- Updating for chef instructors:

Chef instructors use the two best chef instructors' strategies to hone their culinary skills. At first, they try to acquire chef educator methods by imitating the best elite agent. This plan describes the global exploration and capabilities of the CBOA. The primary benefit of this upgrade is that before instructing candidate solutions, chef educators may test their skills against the best chefs. This method allows for the upgrading of candidate solutions, not only the most gifted individuals. By doing this, it prevents the algorithm from being stuck in the local optimum and promotes more precise and effective scanning over the many search space regions. In this example, freshly established cooking teacher posts are filled using Eq. (35).

$$sx_{a,b}{}^{(CFS)} = sx_{a,b} + rand \cdot \left(BestC_b - Ind \cdot sx_{a,b}\right) \quad (35)$$

$sx_{a,b}{}^{C}F\ S$ specifies the first strategy for switching chef instructors, and CFS indicates the new role for the ath-ordered member in the bth manage. The best chef instructor in the bth coordinate, or SX_1 in the SX matrix, is represented by $BestC_b$. I nd is a randomly chosen number from the set {1,2}, and rand is an arbitrary number in the interval [0,1]. Eq. (36) is used to determine this condition:

$$SX_a = \begin{cases} SX_a^{(CFS)}, SFit_a^{(CFS)} < Fit_a \\ SX_a,\ else \end{cases} \quad (36)$$

In this equation, $SFit_a^{(CFS)}$ displays the objective function of $SX_a^{(CFS)}$, and Fita is the fitness function ath member. Based on the second method, each culinary teacher strives to develop their abilities via individual practice. This method intends to increase CBOA's exploitation capabilities and local search. Every elite agents culinary expertise identifies the factors needed to get the aim function's ideal value. This updating technique is beneficial since every person searches for better opportunities in the vicinity, independent of the location of other community members. This idea is to use Eqs. (37) to (38) to produce a random position around each culinary instructor in the search space for each issue variable $b \in [1, dim]$. If this random site increases the goal function's value, it can be updated. Eqs. (39) to (40) are used to model this scenario.

$$LOW_b^{(loca)} = LOW_b^{(local)}/iter \quad (37)$$

$$UP_b^{(local)}/iter \quad (38)$$

Here, $LOW_b^{(local)}$and $UP_b^{(local)}$ show the local boundaries of the bth issue variable, where $iter$ is a parameter for repetition.

$$sx_{a,b}^{(CSS)} = sx_{a,b} + LOW_b^{(local)} + rand.\left(UP_b^{(local)} - LOW_b^{(local)}\right), j-1, NC, J = 1, \ldots, dimm \quad (39)$$

$$SX_a = \begin{cases} SX_a^{(CSS)}, SFit_a^{(CSS)} < Fit_a \\ SX_a, else \end{cases} \quad (40)$$

$SX_a^{(CSS)}$ is the new location for the ath-ranked membership according to the chef's next strategy called $C\ SS$, $sx_{a,b}^{(CSS)}$ displays its bth manage, and $SFit_a^{(CSS)}$is the goal variable value.

Step 2- candidate solutions ' updates As per the CBOA, candidate solutions pursuing culinary arts use these three methods to enhance their cooking abilities:

A chef trains each student, randomly assigning them to a class. This method has the benefit of having a chef mentor the pupils, which helps them acquire new skills. It alludes to users who have moved to the other search zone in the technique. If the best chef instructor teaches pupils, on the other hand, there won't be a worldwide search since there will be a computational bias in favor of the best. The guidance and training of the elite agent determine each culinary student's new role. This situation is expressed in Eq. (41).

$$sx_{a,b}^{(SFS)} = sx_{a,b} + rand \cdot \left(CI_{R_{a,b}} - Ind \cdot sx_{a,b}\right) \quad (41)$$

Based on the learner's initial strategy, known as SFS, the updated position for the ath-sorted member is expressed as $sx_{a,b}^{(SFS)}$, where $CI_{R_{a,b}}$ is the elite agent and R is an arbitrary index in the interval $[0, NC]$. New locations are found using Eq. (42).

$$SX_a = \begin{cases} SX_a^{SFS}, SFit_a^{(SFS)} < Fit_a \\ SX_a,\quad else \end{cases} \quad (42)$$

$SFit_a^{(SFS)}$ is the ultimate value for SFS.

The CBOA's technique involves treating every factor as a skill. Each student learns and mimics one of the chef instructor's skills. An instructor chosen at random from the collection CI_R is used (R is selected from $[1, NC]$). This is comparable to changing just one variable instead of every possible answer in terms of algorithms. This enhances global exploration and search. In order to recreate this situation, the first lead instructor, represented by the CI_{R_a} vector, is randomly selected for each culinary learner sx_a (a CBOA member selected at random from Ra's index

from $[1, NC]$). To represent a talent of the selected head instructor, the cth coordinate of the vector of sx_a, the culinary pupil, is picked at random from $[1, dim]$. CI_{R_c} is this value. In this case, Eq. (43) may be used to calculate the new location:

$$sx_{a,b}^{(SSS)} = \begin{cases} CI_{R_{a,b}}, & b = c \\ sx_{a,b}, & else \end{cases} \quad (43)$$

where b is the problem size ($[1, dim]$), a matches the population and takes a value in the range of $[NC + 1, NC + N]$, c is a random integer selected from $[1, dim]$, and SSS is the student's next strategy. Consequently, the location update is established using Eq. (44).

$$SX_{a,b} = \begin{cases} SX_a^{(SSS)}, FitS_a^{(SSS)} < Fit_a \\ SX_a, else \end{cases} \quad (44)$$

$SX_i^{(SSS)}$ relates to the new position of ath ranked member based on SSS.

Using one of the two last methods, personal activities or research, each culinary student aims to grow personally. This is the algorithm's exploitation stage. The benefit of this approach is that it makes local search stronger while also allowing the algorithm to find more practical answers that are closer to previously discovered solutions. When every obstacle is viewed as a skill, kids will work to improve these skills in order to become more fit. Thus, Eq. (45) is used to find new locations.

The selection of HGSO, CGO, and CBOA stems from their distinct abilities to enhance exploration and exploitation during model optimization critical in high-dimensional, nonlinear domains like diabetes prediction. HGSO draws on thermodynamic principles to escape local optima, improving convergence reliability. CGO leverages fractal-inspired chaotic dynamics, offering effective global search in complex spaces. CBOA mimics human learning strategies to balance global and local refinement. While these optimizers are general-purpose, their adaptability makes them suitable for fine-tuning model parameters in sensitive health-related tasks. These schemes were integrated to boost classification performance beyond what standalone models achieve. Although formal ablation studies were not conducted here, the comparative evaluation highlights clear improvements in predictive metrics, justifying their inclusion.

$$sx_{a,b}^{(STS)} = \begin{cases} sx_{a,b} + LOW_b^{(local)} + rand \cdot \left(UP_b^{(local)} - LOW_b^{(local)}\right) \\ sx_{a,b}, \ else \end{cases} \quad (45)$$

where r dim is a random number chosen from $[1, dim]$ and $sx_{a,b}^{(STS)}$ displays the updated calculated state of the ath member based on the student's third strategy (STS). Eq. (46) displays the changes:

$$SX_{a,b} = \begin{cases} SX_a^{(STS)}, & FitS_a^{(STS)} < Fit_a \\ sx_{a,b}, else \end{cases} \quad (46)$$

Fit $SX_a^{(STS)}$ displays the desired function value of $SX_a^{(STS)}$ as STS. Culinary learners and elite agents discuss $CBOA$ tactics.

2.7 Performance evaluator

A variety of indicators are utilized to assess classifier performance. The term "accuracy" refers to the proportion of accurately predicted observations. Three commonly used metrics are recall, accuracy, and precision. Total accuracy, which encompasses both real negatives and positives, is referred to as accuracy. Unbalanced datasets can lower accuracy. Recall finds only positives and assumes minimal mistakes. The F1 score is helpful in schools with different distributions since it balances recollection and accuracy. It can handle both false negatives and real positives. These measures assist in estimating the efficacy of ML schemes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (47)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (48)$$

$$\text{Recall} = \text{TPR} = \frac{\text{TP}}{\text{P}} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (49)$$

$$\text{F1 score} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (50)$$

where in the further analysis the sign TP designates the case of a positive forecast of the good luck, FP - the abbreviation of fall positive - is used in the case when the outcome of a case is bad. In the case when the forecast is negative and the real result is really negative TN gives the same result. The FN means a bad forecast when the real result is good.

3 Result and discussion

The results obtained from these hybrid schemes are represented comprehensively with various graphs and tables. These tools systematically compare and contrast each model's performance for an in-depth assessment of the functions of each model. From a careful study of the results represented in the graphs and tables, insightful analysis is performed to identify the best model that performs well in terms of predictive accuracy and suitability for the prediction process. Moreover, this review also points out schemes with flaws or limits, adding a critical perspective to the work, especially in respect of their applicability to real-life scenarios. This strong assessment methodology allows researchers to make informed decisions on model selection and optimization for prediction tasks, helping to advance not only the science but also practical applications behind predictive modeling.

3.1 Convergence curve

The convergence curve has a significant influence on prediction processes since it displays the rate at which a scheme learns. A steep slope in the convergence curve displays that convergence happens fast, and hence, the

model quickly learns the pattern and forecasts stabilize. In contrast, a shallow curve indicates slower convergence, which means the model takes longer to comprehend patterns, and hence, the predictions are highly unpredictable throughout training. This helps to understand this curve for optimizing the training tactics and finding a balance between underestimating and overfitting. The suggestions made include those of learning rate changes, batch size changes, and model topology for best prediction performance with no convergence or wasted time in unnecessary training. The convergence curve in Fig. 3 illustrates and compares the results of the hybrid schemes presented. Fig. 3 displays the convergence behavior of each hybrid model across iterations, revealing learning stability and showing which schemes reach optimal accuracy most efficiently during training. It can be seen from this figure that, among the LDCB, LDCG, and LDHG schemes, the LDCG model, which has reached an accuracy of 0.930, has been outperformed by the LDCB model with 0.968 accuracy, whereas its accuracy is higher than that of the LDHG model, which stands at 0.921. Similarly, among the GPHG, GPCG, and GPCB schemes, the GPHG schemes showed an accuracy of 0.942, proving that their accuracy is the lowest compared to the GPCG model, which had an accuracy of 0.960, and the GPCB model, which had an accuracy of 0.980. Their optimal condition was achieved after 60 cycles.

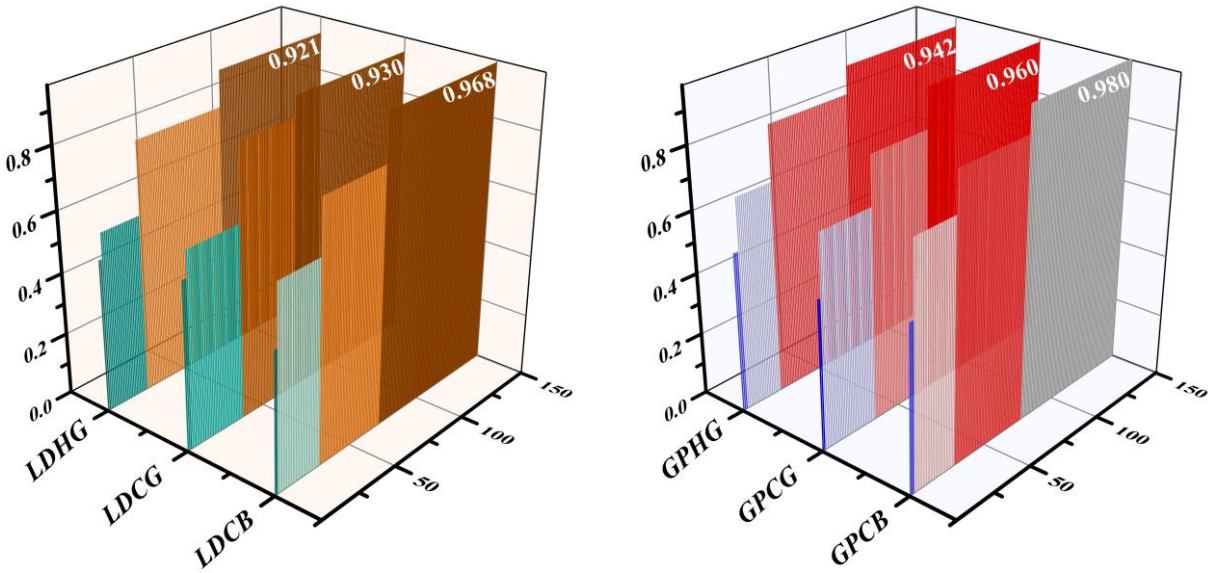


Figure 3: 3D The convergence curve for the 3 schemes

3.2 Schemes comparison

Table 1 displays the outcomes of both the LDR and GPC schemes, as well as their respective hybrid forms in different phases. Table 1 summarizes the accuracy, precision, recall, and F1-scores of all models during training, testing, and overall phases, enabling side-by-side evaluation of classifier performance. In the training phase, it becomes apparent that the functionality of the LDR model, boasting an accuracy of 0.916, falls short than another base model, GPC, achieving 0.937 accuracy in the same phase. Similarly, its hybrid counterpart, the LDHG model, with an accuracy of 0.926, also lags behind the GPHG model with 0.946 accuracy. Furthermore, the precision value of the GPCG model, reaching 0.963, outperforms the precision value of the LDCG model, which stands at 0.935, during the training phase.

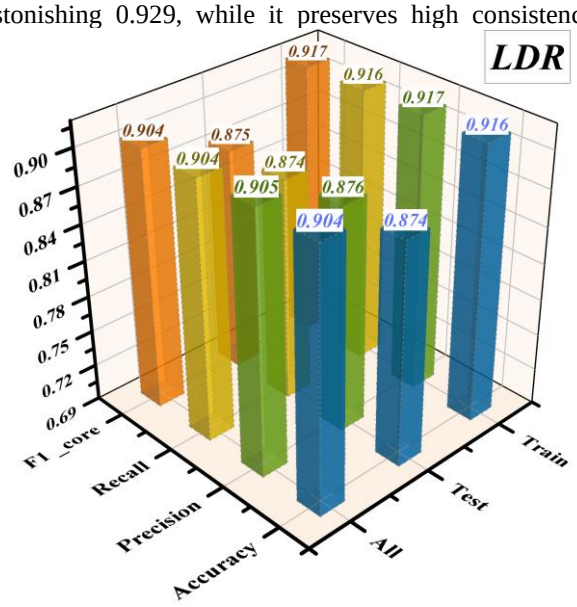
Upon comparing the outcomes of the schemes during the testing phase, it becomes apparent that the recall value of the hybrid forms of GPC schemes exceeds that of the hybrid form of the LDR model. Specifically, during the testing phase, it is evident that LDCG, with a recall value of 0.922, demonstrates weaker functionality than GPCG, which achieves a recall value of 0.957. However, following the LDCB model with a recall value of 0.961, the LDCG model boasts the highest value among its group members. Conversely, GPCG, with a recall value of 0.957, signifies that its performance surpasses that of the GPHG and GPC schemes, which have recall values of 0.935 and 0.909, in that order, although it does not outperform GPCB, with a recall value of 0.978, during the testing phase.

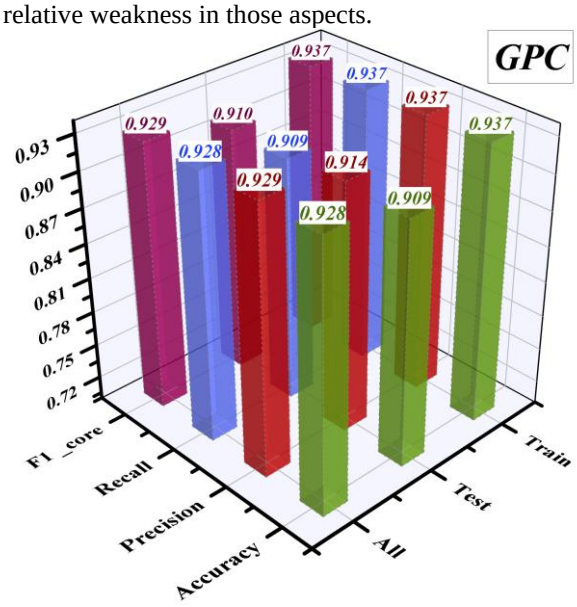
Table 1: The outcome of the showcased developed schemes

Section	Model	Metric values			
		Accuracy	Precision	Recall	F1-score
Train	LDR	0.916	0.917	0.916	0.917
	LDHG	0.926	0.925	0.926	0.925
	LDCG	0.935	0.935	0.935	0.935
	LDCB	0.972	0.972	0.972	0.972

	GPC	0.937	0.937	0.937	0.937
	GPHG	0.946	0.947	0.946	0.946
	GPCG	0.963	0.963	0.963	0.963
	GPCB	0.981	0.981	0.981	0.981
Test	LDR	0.874	0.876	0.874	0.875
	LDHG	0.913	0.913	0.913	0.913
	LDCG	0.922	0.921	0.922	0.921
	LDCB	0.961	0.961	0.961	0.961
	GPC	0.909	0.914	0.909	0.910
	GPHG	0.935	0.937	0.935	0.936
	GPCG	0.957	0.961	0.957	0.957
	GPCB	0.978	0.979	0.978	0.978
All	LDR	0.904	0.905	0.904	0.904
	LDHG	0.922	0.922	0.922	0.922
	LDCG	0.931	0.931	0.931	0.931
	LDCB	0.969	0.969	0.969	0.969
	GPC	0.928	0.929	0.928	0.929
	GPHG	0.943	0.944	0.943	0.943
	GPCG	0.961	0.962	0.961	0.961
	GPCB	0.980	0.981	0.980	0.980

The 3D wall plot of Fig. 4 visualizes model accuracy comparison across three different phases, namely Training, Testing, and All. By taking into account the performances for all the phases of three schemes, a number of thrilling trends can be found out. First and foremost, during the All phase, the LDR model performed best among them with a marvelous score of its precision metric 0.905, which really exhibits the competency of this model with a touch towards precision. With that said, GPC outcompetes all its contenders during the same stage with outstanding precision and F1 score records at an astonishing 0.929, while it preserves high consistency between its measures, which remain around 0.928 with regard to both accuracy and recall, demonstrating an overall robust behavior in performance. In sharp contrast, the LDHG model displays very consistent results in all four metrics, reaching a stable performance of 0.922 in all, reflecting a balanced performance considering different evaluation standards. In contrast, the GPHG model has strengths and weaknesses mixed up on the metrics. Although it has a very commendable score in the precision metric of 0.944, the value is low in other metrics, having 0.943 for accuracy, recall, and F1 score, showing its relative weakness in those aspects.





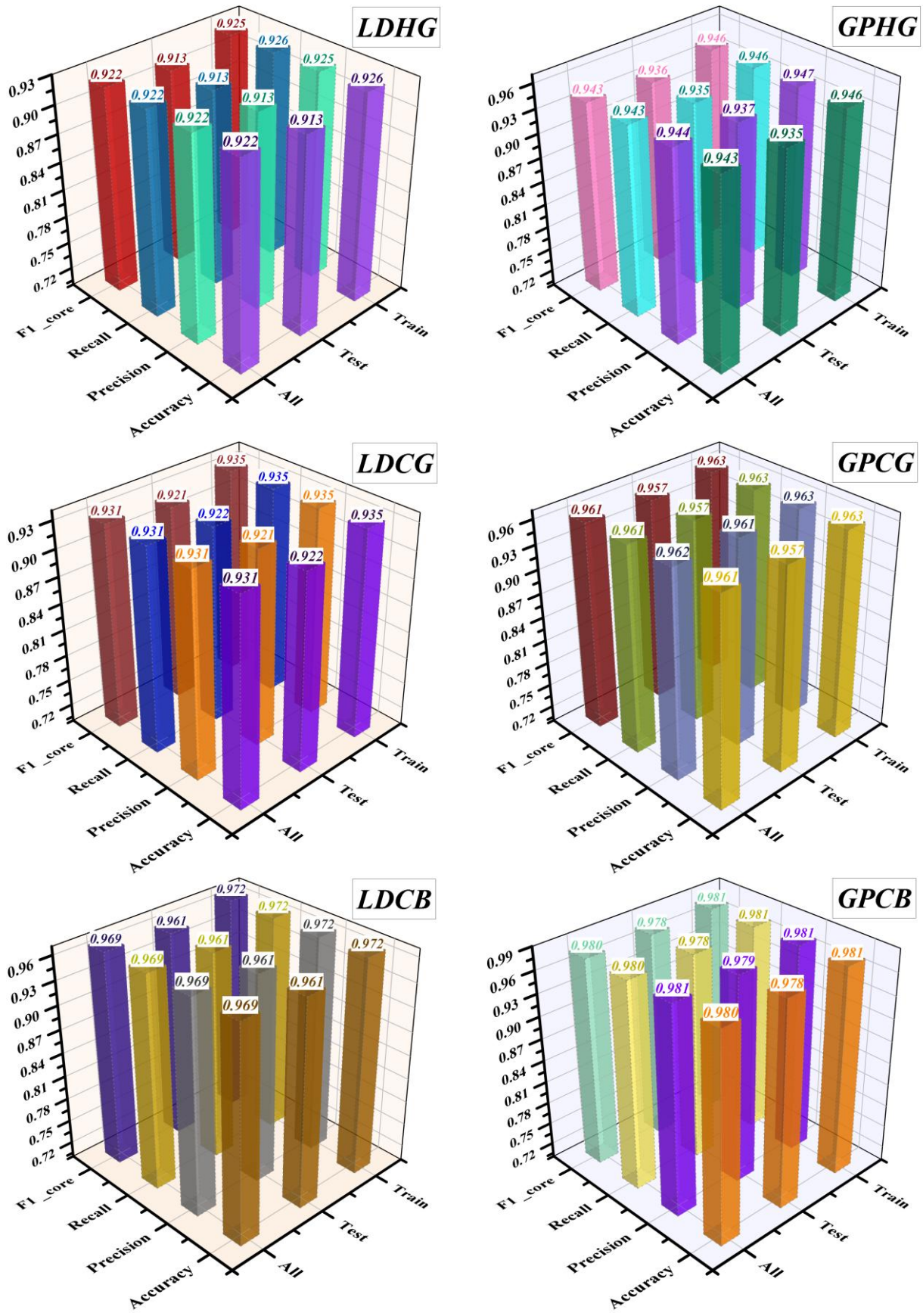


Figure 4: 3D Walls-plot for the performance of the schemes across phases

Table 2 presents a comparison of the functional performance of schemes under both healthy and diabetes conditions. For instance, the LDR model showcases an accuracy of 0.93 under healthy conditions, aligning with

the precision value of the LDHG model. However, the LDCB model emerges as the top performer with a precision value of 0.97, indicating its superiority over the LDCG model, which achieves a precision value of 0.94, as well as other preceding schemes. Among the hybrid versions of the GPC model, the GPCB and GPCG schemes emerge with the highest accuracy under healthy conditions, boasting precision values of 0.99 and 0.98, respectively. Following closely, the GPHG model achieves a precision value of 0.97, while the GPC model records a precision value of 0.95, indicating slightly weaker functionality compared to the former schemes. Nevertheless, the hybrid forms of the GPC model showcase superior functionality in contrast to the LDA scheme and its variants.

Furthermore, under diabetes conditions, the LDCB model exhibits a higher recall value of 0.95, surpassing the recall values of the LDCG, LDHG, and LDA schemes, which stand at 0.90 and 0.88, in that order. Moreover, the recall value of the LDCB model exceeds that of the GPC and GPHG schemes, which are 0.91 and 0.94, respectively. However, it falls short of surpassing the recall values of the GPCG and GPCB schemes, which are 0.96 and 0.98, respectively.

Table 2: Categorization of assessment criteria for the performance of the developed schemes

Metric values	Condition	Model							
		LDR	LDHG	LDCG	LDCB	GPC	GPHG	GPCG	GPCB
Precision	Healthy	0.93	0.93	0.94	0.97	0.95	0.97	0.98	0.99
	Diabetes	0.85	0.90	0.91	0.96	0.88	0.90	0.93	0.97
Recall	Healthy	0.92	0.95	0.95	0.98	0.94	0.94	0.96	0.98
	Diabetes	0.88	0.88	0.90	0.95	0.91	0.94	0.96	0.98
F1-score	Healthy	0.93	0.94	0.95	0.98	0.94	0.96	0.97	0.98
	Diabetes	0.86	0.89	0.90	0.95	0.90	0.92	0.95	0.97

The column line symbol plot in Fig. 5 provides a comparison between the values recorded in both healthy and diabetic situations and the values predicted by the schemes. Under the diabetes condition, it is evident that the LDCB model, with 254 out of 268 measured values, demonstrates higher accuracy than the LDCG model, which achieves 240 out of 267 measured values. Similarly, the base model, LDR, performs better with 236 out of 268 measured values compared to the LDHG model, which also achieves 236 out of 268 measured values. Conversely, under the healthy condition, both GPC and GPHG schemes achieve 468 and 471 out of 500 measured values, respectively, indicating lower accuracy compared to the GPCG and GPCB schemes, which achieve 480 and 491 out of 500 measured values, respectively. Besides, the GPCG and GPHG schemes attain values of 258/268 and 253/268, respectively, under the diabetes condition, which indicates moderate performance by the GPCB model, with attained values of 262/268, and the GPC model, at 245/268.

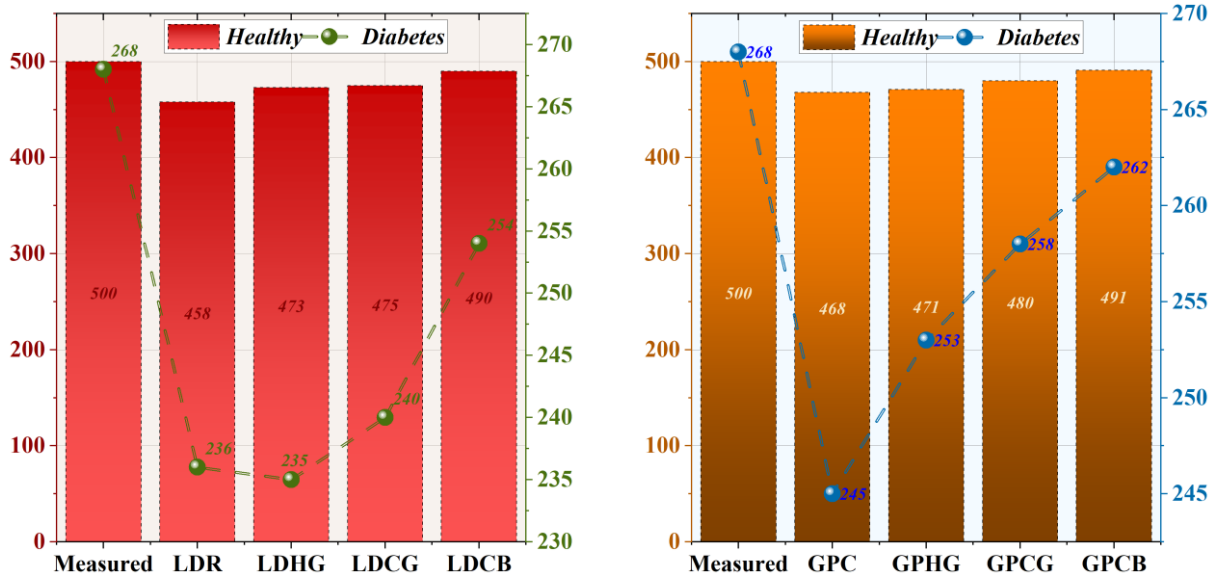


Figure 5: Column-line symbol plot to represent the difference among the schemes

To avoid overfitting, the model's performance was checked at three different phases: training, testing, and overall. Also, the fact that the training and testing measures show the same patterns means that the model is generalizing instead of overfitting. Even though there wasn't a formal validation set, the hybrid schemes' performance in all phases give us an idea of how strong they are. In the future, we will use cross-validation and explicit regularization approaches to better control overfitting and make the model more generalizable.

The ROC is a measure that fundamentally depends on how well binary classifiers work. It compares the false positive rate (1-specificity) to the true positive rate (sensitivity) at various thresholds. This graph conveys useful information about the capability of the classifier to differentiate classes in all possible threshold settings. The ROC is a tool that actually enables the researchers to study the compromise between true positives and false positives, thus giving a complete view of the efficiency of the classifier. Besides, the ROC's AUC gives a quantitative measure of the discriminatory power of a classifier, where larger AUC means better performance. Also, the ROC plot allows for better selection of the optimal cut-off value to classify the samples according to the needs of the specific application, considering sensitivity and specificity to get the same result desired. Therefore, the ROC curve displays a very important means for testing, comparing, and fine-tuning binary classification schemes, thus contributing to enhanced ML model predictive power in a slew of applications. Moreover, in Fig. 6, the outcomes of the suggested schemes are carefully analyzed with the help of the ROC curve, which is a perfect inseparable tool used to analyze the performance of the classifier. It is observed, upon detailed analysis, that GPCB and GPCG are ahead of their competitors in reaching a TPR value of 1.0 at an earlier stage and hence delivers exceptional performance in classification problems. After that, LDCB and GPHG come very close as the second and third schemes, reaching a TPR of 1.0 just a little later but with a sharp increase, further establishing their effectiveness. In sharp contrast, the LDR model lags far behind its counterparts since its vector has the gentlest slope among the compared schemes. Nevertheless, the LDR model eventually attains 1.0 TPR but takes its time in comparison with the others. The above analysis displays how different schemes may perform to the extent and also how often the ROC curve proves useful for making subtle choices regarding classifier behavior, which might not be immediately apparent in other forms, and helps drive better decisions for predictive modeling tasks.

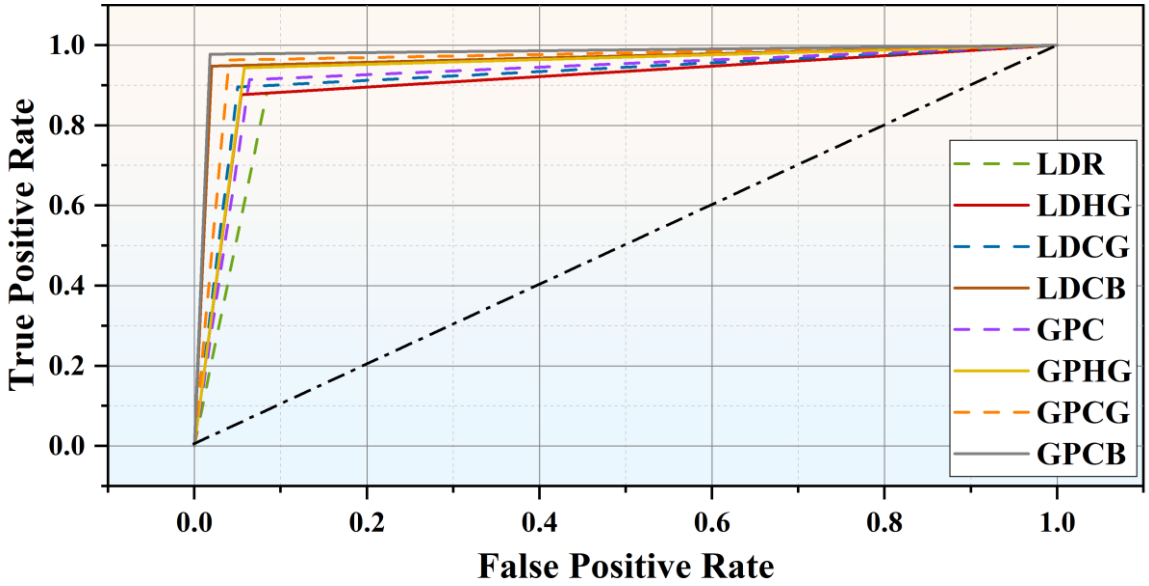


Figure 6: ROC curves depict the performance of the most efficient hybrid schemes

The SHAP additive explanations in Fig. 7 depict the effects of various factors such as glucose or BMI indicators that influence the possibility of diabetes. The following explanation succinctly defines the effects of such factors on the occurrence of diabetes.

- High levels of blood glucose, normally due to excessive consumption of sugar or reduced action of insulin, may eventually lead to the development of diabetes. Blood glucose that remains high over a continuous period places a load on the pancreas secreting insulin, and, with time, may make it lose its efficiency. This can result in insulin resistance-a condition whereby cells become unable to efficiently act in response to insulin signals, causing more accumulation of glucose. Besides, high levels of glucose can cause the damage of blood vessels and neurons, which raise the risk of complication development in diabetic patients. Hence, keeping blood glucose within the norm through proper nutrition, regular physical activity, and medication is considered a significant approach to diabetic prevention and management. BMI, which is determined using weight and height measures, is another widely accepted indicator of body fatness associated with the risk of developing diabetes.
- A high BMI means excess adipose tissue interferes with insulin action, apart from increasing the inflammatory component, leading to insulin resistance and impaired glucose tolerance. The underlying fat also secretes hormones and cytokines, further dampening metabolic processes and increasing diabetes risk. Also, a higher BMI is more often than not associated with other risk factors like sedentary lifestyle and lousy food, increasing the chances of diabetes. By enhancing insulin sensitivity and overall metabolic health, dietary and activity changes that control body mass index (BMI) can lower the risk of diabetes. Therefore, maintaining a

healthy BMI is crucial for both preventing and treating diabetes.

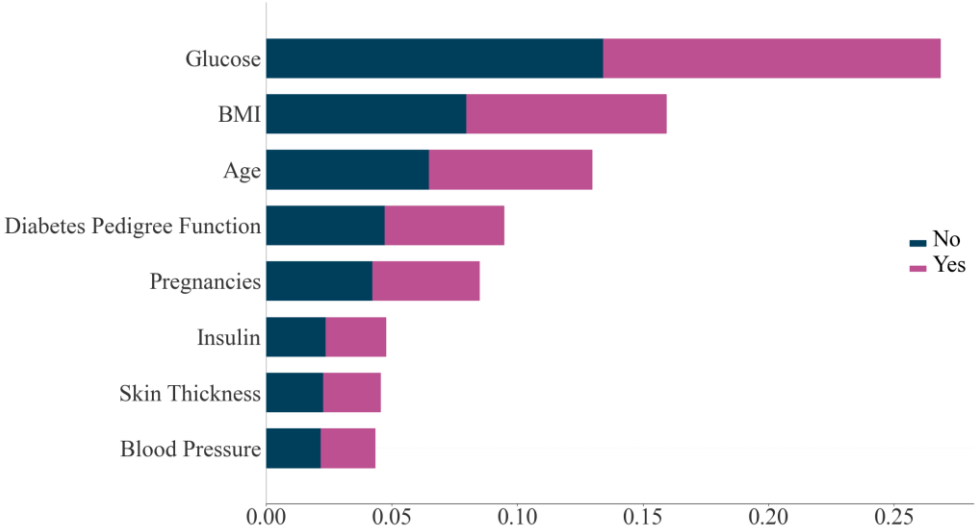


Figure 7: The sensitivity analysis results

Table 3 provides the results of a 5-fold cross-validation for the GPC and LDR models, assessing their stability and generalization across different subsets of the dataset. Each fold (K1 to K5) represents an independent split where the model was trained on 80% of the data and tested on the remaining 20%. The GPC model demonstrates consistently high performance across all folds, with accuracy values ranging from 0.916 to 0.928, indicating strong generalization and low variance. In contrast, the LDR model shows slightly lower accuracy across all folds, with values ranging from 0.887 to 0.904. The results clearly suggest that GPC outperforms LDR not only in individual experiments but also in terms of cross-validated reliability. These findings reinforce the robustness of GPC for diabetes prediction tasks under varying training-test partitions.

Table 3: K-fold cross validation.

Models	**K Fold Number**				
	K1	***K2***	***K3***	***K4***	***K5***
GPC	0.920	0.927	0.924	0.916	0.928
LDR	0.887	0.895	0.901	0.896	0.904

Table 4 presents the results of the Wilcoxon signed-rank test conducted to compare the performance differences between baseline classifiers and their hybrid optimized variants. The test evaluates whether observed differences in classification performance are statistically significant. A lower p-value (typically < 0.05) indicates a statistically meaningful improvement. Among the models, the GPCHG scheme achieved a p-value of 0.0348, indicating a statistically significant enhancement over the base GPC model. Similarly, GPCG produced a marginally significant result with a p-value of 0.0679, while others such as GPC-CBOA and LDR-based hybrids did not show statistically significant improvements, as their p-values exceeded 0.1. The stat column represents the test statistic for ranking the difference between paired models. These findings validate that only specific optimizer integrations particularly with GPC deliver meaningful predictive advantages, supporting the selective use of metaheuristics in medical classification contexts like Type 2 diabetes prediction.

Table 4: Wilcoxon test.

Models	stat	P value
GPC	644	2.25E-01
GPC Henry gas solubility optimization	338	3.48E-02
GPC chaos game Optimization	155	6.79E-02
GPC Chef-Based Optimization Algorithm	48	4.39E-01
LDR	1200	2.45E-01
LDR-Henry gas solubility optimization	824	4.39E-01
LDR-chaos game Optimization	675	6.80E-01
LDR-Chef-Based Optimization Algorithm	125	4.14E-01
GPC	644	2.25E-01
GPC-Henry gas solubility optimization	338	3.48E-02
GPC-chaos game Optimization	155	6.79E-02
GPC-Chef-Based Optimization Algorithm	48	4.39E-01

4 Conclusion

The various advantages of early detection of diabetes by using ML are: it enables early interference, thus preventing the development of complications such as cardiovascular diseases and neuropathy; ML algorithms sift through enormous volumes of data to spot patterns that are so subtle they could indicate diabetes risk, hence improving their accuracy. This will, therefore, be enabling personalized treatment plans for better patient care. Also, automating diagnostics cuts down the healthcare costs and workload for medical staff. In a nutshell, ML aims at early diabetes detection, providing an improvement for patient outcomes through easy healthcare access, thus adopting a proactive stance towards the disease's management.

However, this work aims to project diabetes using ML schemes comprising GPC and LDA, coupled with 3 optimizers: Henry Gass Solubility Optimization, Chef Base Enhancement Algorithm, and Chaos Game Optimization. With the view of improving the accuracy of the prediction, it was decided to couple the schemes with the optimizers. These results mean that the model GPC and its hybrid forms provide better performance than the LDA scheme and its hybrids. Comparing results in GPC, GPHG, GPCG, and GPCB, for instance, out of these, the best result was from the GPCB model in the "All" phase, with an accuracy value of 0.980. In that respect, the GPCG model stands out as the second-best model with an accuracy of 0.961, while the GPHG model gives medium performance in this comparison, with an accuracy of 0.943. In this comparison, the GPC model has the weakest functionality, with an accuracy of 0.928.

- **Limitations:**

There are several drawbacks to projection using ML techniques. The most critical problem of overfitting that most schemes biased the training data and gather noise rather than underlying patterns, which is poor in generalization in unknown data. When the schemes are relatively simple to represent the complexity of the data, underfitting happens with poor accuracy in the forecast. Biases in training data can persist in ML schemes, leading to biased forecasts, especially in sensitive domains like healthcare and criminal justice. Furthermore, ML algorithms need big, high-quality datasets for training, which are not always available, especially in specialist sectors or when dealing with sensitive data. The dynamic nature of real-world data makes it challenging to sustain model correctness over time; hence, regular monitoring and updating become necessary. To solve these limitations, several methods have been tried to reduce overfitting, such as regularization; feature engineering to make the schemes perform better; and algorithms that are fair-aware to reduce biases. All of the above can be further improved by enhancing openness and interpretability of schemes, thus building trust and enabling their adoption in applications of importance. This calls for more research and development on these issues so that the MLC forecasts become increasingly accurate and dependable.

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A Comprehensive Evaluation Model for the State of Electric Energy Metering Devices Based on Fuzzy Analytic Hierarchy Process

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Keywords: fuzzy analytic hierarchy process, electric energy metering device, state evaluation, comprehensive evaluation model

Received: July 17, 2025

Accurately evaluating the status of electric energy metering devices is the foundation for ensuring their stable operation on smart grids, and is conducive to the development of equipment management towards refinement and intelligence. This article proposes a comprehensive evaluation model through the fuzzy analytic hierarchy process (F-AHP), which is characterized by establishing a multi-index system and taking into account subjective opinions and objective data, thereby improving the scientificity of its evaluation and enhancing its anti-interference ability. It starts with establishing a hierarchical structure, dividing the functions of indicators such as structural reliability, measurement accuracy, communication stability, and environmental adaptability. Then, based on the fuzzy decision matrix assignment, the importance of each indicator is calculated, and the assignment and overall score of the indicators are obtained, completing the quantitative evaluation of the health of the measuring device. In the experimental verification, 50 typical electric energy metering device samples were selected for state evaluation modeling. The average CI value of the model was 0.016, the coefficient of variation CV was 0.069, and the accuracy of state recognition reached 92.5%. The evaluation results have high stability, can effectively identify boundary fuzzy samples, and have strong robustness and practical value. The results indicate that the evaluation model proposed in this article can better solve multiple practical cases and the overall evaluation error does not exceed 5%; Compared with traditional AHP and weighted average method (WAM), this model performs better in state recognition accuracy and boundary blurring processing ability. Simultaneously conducting noise experiments and sensitivity analysis, and proving that the model has high stability and reliability under various abnormal conditions.

Povzetek: F-AHP model z večkazalčno hierarhijo izboljša ocenjevanje stanja merilnih naprav, združuje subjektivne in objektivne podatke ter krepi robustnost. Na 50 vzorcih doseže 92,5-odstotno točnost, nizko varianco ter boljšo prepoznavo mejnih primerov.

1 Introduction

With the development of smart grids, the position of energy metering devices in the operation and production of power grid enterprises is becoming increasingly important. They not only serve as the basic unit of measurement for billing and metering, but also perform important tasks such as data collection, load monitoring, and equipment status recognition, playing an important role in ensuring the quality of power supply and serving customer rights. With the rapid development of smart grids and the increasing number of connected devices, it is essential to accurately grasp the operating status of metering devices and be able to detect risks early. However, traditional evaluation methods often rely on human visual inspection or judgment based on a single factor, and cannot provide sufficient measurement scales. The proportion of weights is too subjective and the definition is not clear enough, which cannot adapt to the operation of large-scale equipment.

Different factors can affect the operating status of energy metering devices, such as installation location, wear and tear of components, data transmission quality, power supply quality, and changes in grid noise. There are not only quantitative factors that can be quantified to a single value, but also qualitative evaluation factors that cannot be directly quantified. Whether the instrument interface docking is reasonable is an indicator that cannot be directly measured. Historical data shows that the trend of error rate changes has a strong human explanatory factor. Therefore, it is not easy to simultaneously balance "orderliness" and "fuzziness" using only traditional analytic hierarchy

process or fuzzy mathematics methods. To more accurately and comprehensively characterize the overall working status of electric energy metering, it is necessary to establish a performance evaluation model with clear hierarchy and measurement fuzzy acceptability requirements [3]. This article establishes a comprehensive performance evaluation model using the fuzzy analytic hierarchy process to design a specific evaluation system model for electric energy metering devices in real-world operating scenarios. This model is based on a multi-dimensional evaluation index system and integrates professional knowledge and real-time data. After establishing a fuzzy judgment matrix, determining weights, and conducting consistency checks, it forms a comprehensive evaluation model with clear hierarchy, reasonable weights, and practical effectiveness, thus changing the shortcomings of traditional methods that cannot cope with fuzziness and human factors. Through this model, equipment managers can achieve quantitative diagnosis of equipment operating status, identify operational defects, and assist in developing differentiated maintenance and repair plans.

The structure of this article is arranged as follows: Chapter 2 provides an overview of the research status of existing power measurement equipment status evaluation; Chapter 3 further elaborates on the design ideas and construction methods of the proposed model; Chapter 4 mainly presents the implementation methods and evaluation process of the model; Chapter 5 provides a discussion of an example and presents a comparative analysis of the example, as well as an analysis of the practicality and robustness of the model; The final chapter six provides a comprehensive summary of the research content and prospects for future development directions.

2 Related work

Although energy metering is becoming increasingly important in intelligent power grids, there are still many challenges in identifying and optimizing measurement deviations in energy meters. The various complex and ever-changing environments in which electric energy meters are used make errors in electric energy metering devices not only caused by external electromagnetic interference, nonlinear loads, harmonics, but also by aging of the equipment itself and constraints on design accuracy [4]. Especially in situations where different types of instruments are shared, voltage fluctuations are large, and large amounts of data are transmitted, traditional methods are no longer able to meet the requirements of power network operation efficiency and accuracy. Therefore, researchers hope to find new online inspection methods and self diagnostic models to use digital technology to track the evolution process of monitoring errors [5, 6].

In recent years, the focus of discussions on abnormal energy metering has mainly been on anomaly detection schemes based on feature extraction and modeling, such as equipment operation status classification detection and prediction based on gradient boosting tree (GBDT), grey model, etc. [7]; The second is to use intelligent analysis methods to achieve intelligent determination of device operating status, such as applying deep learning technology to establish multi-sensor models for data anomaly analysis and anomaly source localization [8]; The third is a comprehensive equipment operation status evaluation model formed by integrating multiple decision-making methods such as fuzzy reasoning technology, grey target theory, and analytic hierarchy process.

Some scholars have discussed the challenges of state identification under special conditions such as nonlinear loads and power quality disturbances. For example, Shah (2023) [9] designed an artificial intelligence based nonlinear load detection and identification system, which can reasonably identify power data containing noise and structural abnormalities; Yu et al. (2022) [10] established an online power quality monitoring mode using grey target theory and achieved multi-layer classification and identification of key indicator trends in practical problems. Zhang et al. (2022) [11] also proposed using Software Defined Networking (SDN) to reconfigure the data transmission path for system architecture, in order to ensure the reliability and effectiveness of the acquisition process of electricity metering data under diverse input conditions.

It is worth noting that the application of Fuzzy Analytic Hierarchy Process (FAHP) in power status assessment and evaluation has also received more attention. For example, Taherikhonakdar et al. (2023) [12] used a combination of Fuzzy Analytic Hierarchy Process and Grey System to evaluate the status of 750kV energy metering devices. In F, they classified and rated the measured 750kV energy metering devices, and obtained a more reasonable and comprehensive evaluation result of 750kV energy metering devices. Paunkov et al. (2023) [13] proposed an adaptive correction mechanism for real-time calibration of measurement deviation using fuzzy control rules, which achieved real-time adjustment of measurement deviation and improved the consistency and accuracy of device ratings. From this, it can be seen that the Fuzzy Analytic Hierarchy Process (FAHP) has the advantages of fuzzy analytic hierarchy process due to its consideration of the fuzzy modeling process between multiple factors and the allocation of weights for multiple factors. It is a powerful means to achieve "accurate comprehensive use" state evaluation.

The research on transfer learning and generative models has also expanded the scope of multi characteristic analysis for device state assessment. Alrobaie et al. (2023) [14] utilized a balanced comprehensive evaluation method for power quality issues based on CVAE-TS, which considers the effectiveness and wide applicability of the evaluation method; Qu et al. (2024) [15] used an improved XGBoost to construct an evaluation model for power system stability transfer degree, which has good scalability in multi scenario analysis applications. This has laid a theoretical foundation for the subsequent construction of an adaptive state evaluation mode suitable for power grid measurement devices.

Based on the existing research results, it can be found that the main technologies at present have made certain progress, such as error detection and data processing, but

there are still many areas that urgently need improvement. One is that the current indicator system lacks strict hierarchical relationships and adaptation rules, which limits the performance that can be used in complex situations. The other is that although expert evaluations have a certain degree of reliability and flexibility, cognitive biases or subjective uncertainties may still occur in some situations, and fuzzy mathematical methods need to be introduced to establish quantitative evaluation models. The third issue is that most of the models cannot clearly provide the level classification and visual effects of the results, which affects the effectiveness of the output [16]. In response to these shortcomings, this article establishes a state evaluation model based on fuzzy analytic hierarchy process to establish a hierarchical structure, fuzzy weight reconstruction model, and evaluation model that is easy to understand. Based on fuzzy judgment matrix, consistency analysis, and state level grading standards, it effectively solves the problems of current models in structural design, weight allocation, and result interpretation, and can provide reference for later maintenance plan formulation and maintenance arrangement optimization.

Table 1 compares the performance of existing representative state evaluation methods in terms of data type, evaluation path, accuracy, and robustness. It can be seen that the state evaluation model based on fuzzy analytic hierarchy process (F-AHP) proposed in this article is superior to traditional models in terms of accuracy and applicability, especially in supporting hierarchical output and fuzzy boundary recognition, which provides theoretical support for the subsequent construction of intelligent metering device management and control mechanisms.

Table 1: Comparison between existing methods and the model proposed in this paper

Method Name	**Sample Type**	**Technical Approach**	**Evaluation Metrics**	**Robustness**
GBDT Model [7]	Smart meter time-series data	Gradient Boosting Decision Tree	Single error metric	Moderate
Grey Target Theory [10]	Power quality monitoring data	Grey decision model	Multi-feature trend analysis	Strong
SDN Prediction Model [11]	SDN monitoring and control data	Prediction optimization + graph structure	Communication metrics focused	Fair
FAHP + Grey System [12]	750kV high-voltage equipment	Multi-layer weight fusion	Four state dimensions	Moderate
Proposed Method	Three-phase meters, terminal devices (50 samples)	F-AHP (Fuzzy Analytic Hierarchy Process)	Four-layer metrics + graded evaluation	Strong

This article mainly emphasizes several key issues in the current state evaluation of electric energy metering devices.

Most existing models use a fixed weight superposition method, which has not formed an effective hierarchical structure and failed to reflect the relative importance between indicators. In reality, there are significant differences in the equipment level of each device, and the same evaluation may not highlight individual issues, which reduces the specificity of the evaluation.

Existing research has shown that there is no emphasis on the processing and application of fuzzy information. In the actual evaluation process, many subjective and fuzzy factors, such as "connection standards" and "operational stability", have not been considered in the system design, resulting in fixed thinking in the evaluation results and insufficient response to complex and changing real states.

In terms of evaluating output expression, there is a lack of hierarchical expression, making it difficult to achieve refined management. When promoting and applying on a large scale, the lack of a unified level judgment logic and hierarchical strategy for evaluation can easily lead to monitoring delays and failure to identify risks in a timely manner.

In response to the above issues, improving the scientific construction, fuzzy adaptability, and hierarchical establishment of state assessment models has become the core content of current research. Therefore, this article will focus on the exposition of these two issues as the main line to carry out the research in the following text.

Can the fuzzy analytic hierarchy process balance clear structure and fuzzy information processing to enhance the scientific evaluation of the state of electric energy metering devices?

How to build a multi-level classification system with discriminative power, so that the evaluation model can adapt to the equipment management needs in different application scenarios?

This article proposes a comprehensive state evaluation model based on fuzzy analytic hierarchy process to address the above issues. Its main innovations lie in the following aspects.

Build a multidimensional indicator system that covers key elements such as structure, error, and communication, and allocate weights through FAHP to enhance the hierarchical and explanatory power of the model.

Introduce fuzzy judgment matrix and consistency check mechanism to enhance the ability to accommodate subjective evaluation information and solve the instability problem in traditional AHP applications.

A systematic evaluation workflow was developed and examples were used to verify the effectiveness of the model in identifying weak links and assisting precise management. Experimental results also showed that this model has advantages in stability and adaptability compared to traditional models, and is easier to promote.

3 Design of model construction methods

In the comprehensive evaluation model proposed in this article, the selection of fuzzy analytic hierarchy process as the core method is based on its advantages in dealing with complex and multi-level indicator systems, which combine structural clarity and fuzzy adaptability. Although the traditional Analytic Hierarchy Process (AHP) has good structural modeling capabilities and is suitable for multi factor evaluation problems, it often exhibits limitations such as strong subjectivity and poor consistency of judgment matrices when facing practical problems such as fuzzy expert cognition and unclear boundaries between indicators. The fuzzy analytic hierarchy process, by introducing fuzzy numbers and fuzzy judgment matrices, not only retains the hierarchical logical structure of AHP, but also significantly enhances the model's ability to accommodate fuzzy information, improving the stability and practicality of comprehensive evaluation.

This model divides the comprehensive status of electric energy metering devices into three levels: target level, criterion level, and indicator level. The target layer is the comprehensive status of the electric energy metering device, while the criterion layer includes four key attributes: structural reliability, measurement accuracy, communication stability, and adaptability to operating environments, The indicator layer is further refined into more than ten quantifiable or determinable specific indicators (such as error drift rate, wiring standardization, signal packet loss rate, etc.). There are significant attribute differences and cognitive ambiguity among various indicators, making it suitable to use triangular fuzzy numbers to construct a judgment matrix and calculate relative weights and comprehensive scores.

Compared with traditional single weighted sum methods, FAHP has the following advantages: firstly, it allows experts to use fuzzy language (such as "slightly higher" or "significantly stronger") to evaluate when constructing the judgment matrix, and improves the flexibility and closeness of judgment through fuzzy number transformation; Secondly, FAHP introduces the maximum membership degree and fuzzy consistency check mechanism in the weight calculation process, which can effectively reduce the impact of subjective errors on the evaluation structure, thereby improving the consistency and robustness of the evaluation model.

The difference between FAHP and evaluation models such as weighted average, entropy weight, and TOPSIS is that FAHP can more clearly, accurately, reasonably, and intuitively handle such problems when multiple indicators coexist and subjective and objective factors are intertwined. When the equipment conditions become increasingly diverse and complex, and there is a certain degree of ambiguity in expert evaluations, the advantages and superiority of this method in weight setting and result description will be fully reflected. In addition, this method does not require too much historical data and complex optimization algorithms to support, so it can be well applied to online monitoring systems or distributed management systems, which greatly improves its computing speed and applicability.

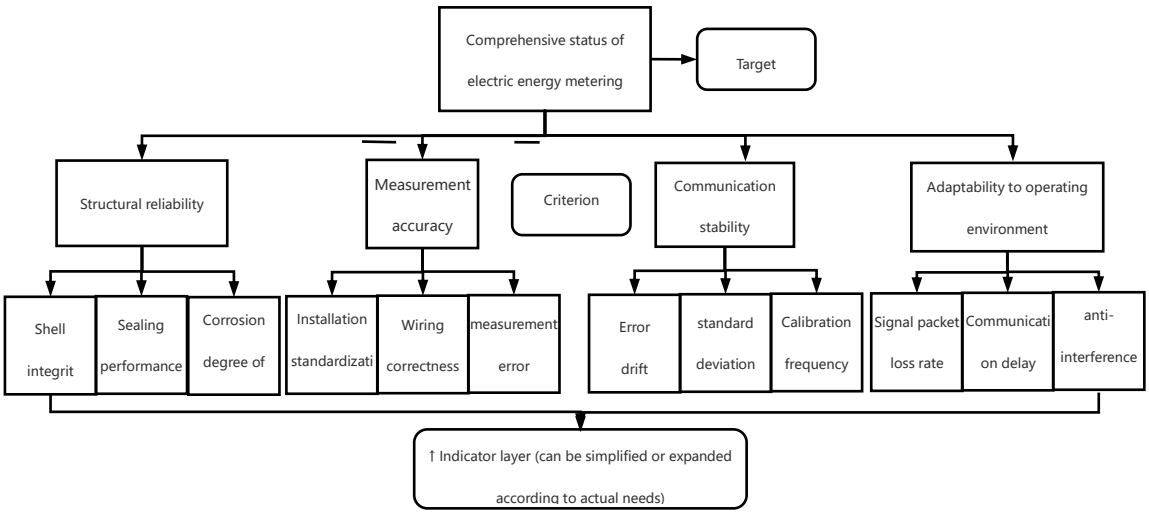

Figure 1：Structure diagram of comprehensive state evaluation model for electric energy metering devices based on fuzzy analytic hierarchy process (F-AHP)

As shown in Figure 1, this article uses the Fuzzy Analytic Hierarchy Process (F-AHP) to construct a multi-level hierarchical structure consisting of the objective layer, criterion layer, and indicator layer. It integrates fuzzy judgment matrix, weight extraction, and consistency check to achieve comprehensive evaluation of multi-source indicator information.

3.1 Construction of state indicator system for electric energy metering devices

This article uses the Analytic Hierarchy Process (AHP) to evaluate the overall situation of power metering devices, and constructs a clear logical hierarchical model to analyze the overall state of power metering devices during operation. Based on this, three different modules are formed, including the target layer, criterion layer, and indicator layer. Its core function is to transform the fuzzy status of power metering device operation and management into a hierarchical system with a systematic structure, and thus become a comparable and computable data system.

At the target layer, the overall operational performance of the measuring device is defined as the evaluation criterion and is the ultimate object of the model. This layer contains four types of primary attribute values, including structural reliability, measurement accuracy, communication stability, and environmental adaptability. These four types of attribute values are the structural performance, metrological performance, communication performance, and environmental adaptability of the measuring device. They cover the main functions of the physical performance, metrological performance, communication performance, and environmental performance of the measuring device, and are all key elements for evaluating the operational quality of the measuring device.

The indicator layer specifically refers to observable indicators. Set indicators such as "external shell integrity", "joint corrosion condition", and "fixed fastening" based on the "structural reliability" index of external structural integrity to measure the true degree of object damage; Set indicators such as "error bounce rate", "standard error degree", and "regular calibration frequency" based on the "measurement accuracy" indicator to measure the measurement accuracy and precision of the instrument on electrical data; Set indicators such as "communication stability" to measure the integrity and timeliness of communication information between equipment and central stations, including "communication delay degree", "data loss ratio", and "noise immunity"; The environmental tolerance index is composed of indicators such as "adaptability to usage environment", "temperature range of working environment", "humidity range of working environment", "anti-interference degree of electromagnetic environment", and "outdoor protection category".

These indicators together constitute the feature vector for evaluating the input of the model. Let the indicator vector of the i-th measuring device be:

$$X_i=[x_{i1},x_{i2}\cdots,x_{in}] \quad (1)$$

Among them, x_{ij} represents the observation or rating value of the i-th device on the jth indicator, and n is the total number of indicators. To eliminate the influence of dimensionality, all indicators will be normalized in the future.

Unlike traditional evaluation methods that simply weight and add various indicators, this paper establishes a judgment matrix based on a fuzzy hierarchical structure for weight extraction, and introduces fuzzy language variables to quantitatively express qualitative indicators, thereby enhancing the model's ability to handle "subjective fuzziness" and "cross indicator correlation".

Table 2：State index system of electric energy metering devices

Metric Name	Dimension Category	Metric Type	Reference Range
Enclosure Integrity	Structural Reliability	Qualitative	Intact / Minor Damage / Severe Damage
Terminal Corrosion Level	Structural Reliability	Qualitative	None / Mild / Severe
Installation Stability	Structural Reliability	Qualitative	Firm / Loose / Detached
Error Drift Rate	Measurement Accuracy	Quantitative	0% ~ 2%
Standard Deviation	Measurement Accuracy	Quantitative	0 ~ 0.05
Packet Loss Rate	Communication Stability	Quantitative	0% ~ 5%
Communication Latency	Communication Stability	Quantitative	0ms ~ 300ms
Noise Immunity	Communication Stability	Qualitative	Weak / Moderate / Strong
Temperature Adaptability	Environmental Suitability	Quantitative	-25℃ ~ +60℃
Protection Rating (IP)	Environmental Suitability	Qualitative	IP20 / IP54 / IP65 etc.

In the entire model system, the selection of indicators follows the principle of "comprehensive coverage, quantifiability, and distinguishability", striving to ensure the evaluation accuracy and discriminative ability of the model while considering the feasibility of the project.

3.2 Principles and applications of fuzzy analytic hierarchy process

This article uses the Fuzzy Analytic Hierarchy Process (FAHP) to solve the multi factor and multi-level uncertainty problems encountered in the overall state evaluation process of power metering equipment. Compared with the traditional Analytic Hierarchy Process (AHP), FAHP based on fuzzy mathematical theory can better adapt to the fuzziness and subjectivity of expert judgment, improving the scientific and robust overall evaluation.

The core idea of FAHP is mainly to model the evaluation level range, construct a fuzzy judgment matrix, calculate fuzzy weight vectors, and perform hierarchical summarization. This method uses the three-sided fuzzy number (l_{ij}, m_{ij}, u_{ij}) to score experts, indicating the weight relationship and objectivity between different indicators, thereby reducing subjective misjudgments caused by human operation. Specifically, it represents the lowest judgment value, and if it is the most likely judgment value, it is the highest judgment value. To achieve fuzzy quantification of subjective judgments, this article adopts a nine-level fuzzy language scale, and its corresponding relationship with triangular fuzzy numbers is shown in Table 3.

Table 3：Mapping table of fuzzy language and triangular fuzzy numbers

Fuzzy Term	Triangular Fuzzy Number (l, m, u)
Equally Important	(1, 1, 1)
Slightly More Important	(1, 2, 3)
Moderately Important	(2, 3, 4)
Clearly More Important	(4, 5, 6)
Strongly Important	(6, 7, 8)
Extremely Important	(8, 9, 10)

Among them, (l, m, u) respectively represent the lower limit, median, and upper limit of the uncertain interval for judgment. Experts use this as a basis for language evaluation when constructing a fuzzy judgment matrix, and further use it for weight calculation and consistency testing.

In the matrix construction stage, the relative weights between each criterion are compared using fuzzy pairwise comparisons to generate a fuzzy judgment matrix, and fuzzy consistency checks are used to ensure that the judgment logic is reasonable. Subsequently, the fuzzy synthesis algorithm is used to calculate the fuzzy weights for each level, and deblurring is applied to convert the fuzzy numbers into clear weight values, ultimately forming a standardized weight vector. This process ensures that the weight allocation of each indicator to the overall state evaluation results is interpretable. To adapt to practical application scenarios, the model also introduces a hierarchical synthesis mechanism, which weights and summarizes the evaluation values of each sub indicator to obtain the comprehensive score of each device's state. At the same time, to avoid extreme value interference, a normalization processing function is set up within the system to standardize the mapping of the original scores, thereby making different devices comparable.

3.3 Hierarchical structure and weight calculation of evaluation model

To achieve a systematic evaluation of the operating status of electric energy metering devices, this paper constructs a three-level fuzzy analytic hierarchy process model. The model structure consists of a target layer, a criterion layer, and an indicator layer from top to bottom, with clear hierarchical logic and comprehensive evaluation dimensions. It can effectively cover multiple key aspects involved in device operation, such as performance, environment, maintenance, and faults.

The target layer is set as the "comprehensive state level of electric energy metering devices", representing the overall goal that needs to be judged ultimately; The criteria layer includes four dimensions: "structural reliability,""metrological accuracy,""communication stability,"and "en vironmental adaptability,Evaluation dimensions are constructed from the perspectives of equipment stability, external environmental resilience, implementation of operation and maintenance systems, and fault susceptibility; The indicator layer is refined into several observable sub indicators, such as measurement accuracy, voltage load response, resistance to temperature and humidity fluctuations, calibration frequency, fault repair cycle, etc., to ensure that the evaluation of each dimension has practical operability and measurement basis.

In the stage of determining model weights, the Fuzzy Analytic Hierarchy Process (FAHP) is used for weight calculation. Firstly, organize multiple experts in power equipment operation and maintenance, as well as measurement technicians, to conduct pairwise comparisons around the elements of the criterion layer and indicator layer, and construct a fuzzy judgment matrix. The relative importance range of each comparison result is expressed as a triangular fuzzy number of (l_{ij}, m_{ij}, u_{ij}), effectively quantifying the fuzziness in subjective judgments. Subsequently, the weight calculation and consistency check are completed through the following steps:

①Fuzzy synthesis weight calculation: using the fuzzy arithmetic mean method to perform fuzzy synthesis calculation on each judgment matrix, obtaining the fuzzy weight vector of each layer element;

②De fuzzification processing: Convert triangular fuzzy numbers into corresponding clear weight values. The commonly used methods are "maximum membership

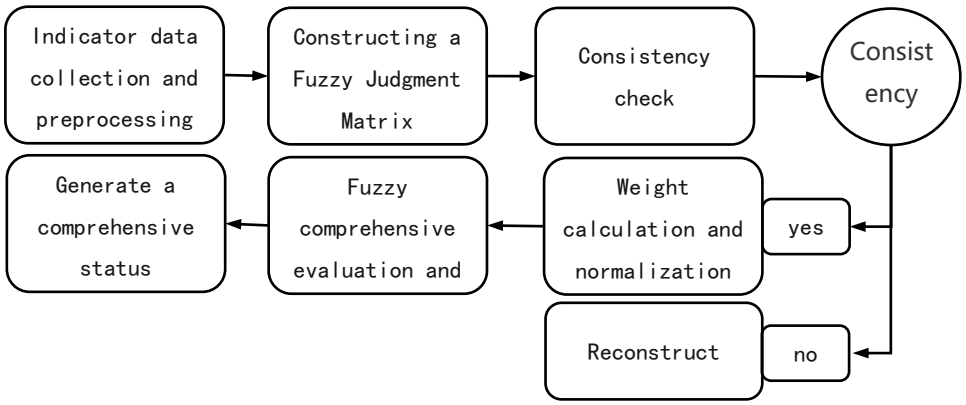

Figure 2：Model implementation and evaluation flowchart

degree method" or "center average method". In this study, the latter is chosen to improve computational efficiency;

③Normalization adjustment: Scale each weight so that the sum of each weight is 1, to ensure comparability and accuracy of the model's weighting calculation.

④Consistency test: Use the CR ratio to determine whether the consistency of each judgment matrix is good. If cr<0.1, it is considered that the consistency of each judgment matrix is excellent and the calculation result is acceptable.

Finally, weighting the elements at different levels in the system and using them as weighting vectors to participate in the fuzzy evaluation system in the following text is beneficial for the classification of power measurement and control equipment status. It not only enhances the scientificity and practicality of the model, but also improves the state analysis and decision-making performance of the measurement and control equipment.

4.1 Indicator data acquisition and standardization processing

The first step in model implementation is to obtain the raw indicator data of the energy metering device. The selected state indicators in this article cover five dimensions: structural reliability, measurement accuracy, communication stability, and environmental adaptability. The relevant data mainly comes from multiple channels such as on-site inspection records of enterprises, online monitoring systems, device self diagnosis modules, and historical maintenance archives, ensuring the comprehensiveness and representativeness of data sampling.

Due to differences in the measurement units and numerical ranges of each indicator, direct use for evaluation may result in weight shift and result distortion. Therefore, it is necessary to standardize the original data. The standardization method is divided into two categories based on indicator attributes: for positive indicators (the larger the value, the better the state), the range standardization method is used:

4 Model implementation and evaluation process

This study constructed a hierarchical comprehensive evaluation model from the data collection layer to the processing layer, and from the evaluation layer to the warning layer. According to its order, it can be divided into: firstly, using a predetermined set of state indicators to collect standardized basic data; Then, construct a fuzzy decision matrix and verify its consistency to ensure that the weights of each indicator value in each layer are reasonable; After the consistency verification is completed, the fuzzy analytic hierarchy process (F-AHP) is used for multi-level data correlation to quantify the membership degree of various electrical measurement and metering equipment states and determine the operating level of the equipment. Fully considering the actual situation of the power grid, it has high applicability and openness. The workflow is shown in Figure 2.

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (2)$$

For negative indicators (the smaller the value, the better the state), use the reverse standardization formula:

$$x_{ij}^{'} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (3)$$

Among them, x_{ij} represents the original value of the jth indicator in the i-th object, and $x_{ij}^{'}$ is its standardized value. This standardization process can unify all indicator data into the [0,1] interval, avoiding interference from numerical dimensions in the calculation of model weights, ensuring the fairness and scientificity of the evaluation system, and laying a data foundation for the subsequent construction of fuzzy judgment matrices and weight analysis.

4.2 Construction of fuzzy judgment matrix and consistency test

On the basis of standardized indicator data, in order to achieve the importance ranking of factors between different evaluation levels, it is necessary to construct a fuzzy judgment matrix and conduct consistency checks. Its core lies in introducing subjective judgment through expert scoring method, while combining fuzzy mathematics to handle ambiguity and uncertainty, to enhance the adaptability and practical operability of the model.

The basic steps for constructing a fuzzy judgment matrix are as follows: Firstly, based on the hierarchical structure model, the importance of each indicator in the same layer is compared pairwise, and a judgment matrix is established by referring to the 1-9 nine level scaling method

$$A=(a_{ij})_{n\times n} \quad (4)$$

Among them, a_{ij}represents the importance of the i-th indicator relative to the j-th indicator. In the fuzzy analytic hierarchy process (F-AHP), the elements of the judgment matrix are represented in the form of triangular fuzzy numbers, namely $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$,representing the lowest possible value, the most reliable value, and the highest possible value, respectively, reflecting the expert's judgment of the importance of the i-th indicator relative to the j-th indicator under uncertain conditions. For example, experts believe that "slightly important" can be represented as a fuzzy number (2, 3, 4), while "extremely important" can be represented as (8, 9, 9). When $\tilde{a}_{ij}$=(l, m, u), its reciprocal can be expressed as (1/u, 1/m, 1/l), satisfying a fuzzy symmetry relationship where they are reciprocal to each other. After completing the preliminary judgment matrix, calculate the eigenvectors and normalize them using the following method to obtain the preliminary weights of each indicator

$$w_i = \frac{\prod_{j=1}^{n} a_{ij}^{1/n}}{\sum_{i=1}^{n}\prod_{j=1}^{n} a_{ij}^{1/n}} \quad (5)$$

To ensure the consistency of the judgment results, it is necessary to perform consistency checks on the judgment matrix. The specific process includes: calculating the maximum eigenvalue λ_{max}, consistency index CI, and consistency ratio CR, where:

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n-1}, \mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \quad (6)$$

Among them, RI is a random consistency index, which is obtained based on its parameter size n and can be directly consulted. If CR<0.10, it indicates that its matrix has met the consistency check requirements; On the contrary, it is necessary to adjust the original assignment and perform another operation. This not only ensures the systematic rigor of the model structure, but also further enhances the credibility of the total weights, and provides a scientific basis for our later fuzzy analytic hierarchy process (F-AHP).

4.3 Calculation of comprehensive evaluation value and classification of status levels

After completing the weight calculation and indicator standardization processing, the most important model evaluation task to be executed next is the allocation of comprehensive evaluation values and state levels. By using the fuzzy analytic hierarchy process (F-AHP), qualitative evaluation is transformed into quantitative evaluation to accurately reflect the status of energy metering equipment.

Based on the constructed weight vector w=(w1, w2,..., wn) and the indicator membership matrix R, use fuzzy operations to comprehensively evaluate and calculate the comprehensive membership vector B.

$$B=W\cdot R=(b_1, b_2, ..., b_m) \quad (7)$$

Among them, B is the overall membership degree of each state level, W is the weight vector, and the membership matrix R is an n × m dimensional matrix, representing the membership values of each evaluation indicator at different state levels, reflecting the degree of fuzziness of the equipment belonging to the four categories of "excellent, good, medium, and poor" on each indicator. The construction method is usually based on expert scoring or fuzzy quantification rules, mapping each original indicator value to the [0,1] interval through a membership function to form a membership vector. For example, a lower communication packet loss rate can correspond to a higher membership degree in the "excellent" state, while in the "poor" state, the membership degree is close to 0. After vertically arranging the fuzzy membership vectors of all indicators, a complete membership matrix R is formed. m is the number of state levels, and the sample is calculated. b_k represents the membership degree of the sample at the kth state level, and the higher the value, the closer the sample is to the kth state level. The weighted sum of membership degrees that can ultimately be used to comprehensively evaluate the value is calculated as follows.

$$S = \sum_{k=1}^{m} b_k \cdot v_k \quad (8)$$

Among them, v_k is the membership value corresponding to the state level, which is generally assigned based on the state level, such as excellent, To achieve quantitative grading of equipment operating status, this article maps the comprehensive score S to four status levels, defined as follows: Excellent (Level I) =4 points, Good (Level II) =3 points, Fair (Level III)=2 points, Poor (Level IV)=1 point. The scoring criteria for each level are shown in Table 2. This assignment scheme adopts linear equidistant scores to reflect the balance of level differences, facilitating weighted operations and membership analysis. At the same time, it has scalability and can be adjusted to a percentage system or non-linear weight structure according to business needs.

Table 4: Comprehensive evaluation values and status classification standards for electric energy metering devices

Comprehensive Score Range	Status Level	Status Description
3.5–4.0	Excellent	Good condition, stable operation
2.5–3.4	Good	Slight fluctuations, basically normal
1.5–2.4	Fair	Operational fluctuations, attention needed
1.0–1.4	Poor	Abnormal condition, maintenance required

The grading criteria in Table 4 refer to the principle of linear distribution and set the scoring interval boundaries based on expert experience and opinions. Due to the final score $S \in [1,4]$ and a total interval length of 3, it is divided into three complete intervals and one compensated low interval (1.0-1.4) using the equidistant method, aiming to improve the recognition sensitivity of "poor" level devices. This design facilitates the implementation of a hierarchical response mechanism and also has good scalability.

5 Analysis of experimental results

This article proposes a model analysis and evaluation based on the fuzzy hierarchy process for the state evaluation of electric energy metering devices. The experimental data is based on real-time data from the power distribution network and includes various operating modes and environmental conditions. By analyzing and comparing the effects of different weights and classification choices on the model, it is proven that the model method proposed in this article can distinguish equipment states and has a better ability to classify equipment. Finally, the experimental results of each stage were analyzed and discussed, and the applicability and stability were explored.

5.1 Experimental data sources and case selection

The case data of this study is selected from the historical archives of the power metering equipment management system, covering various forms such as metering equipment forms, three-phase smart meters, comprehensive substations, and power quality monitoring terminals. It is scattered in the supply and distribution grids of urban and rural areas, presenting significant differences in external environment and load changes. The original data includes eight main indicators including equipment reliability, counting accuracy, connection consistency, communication performance, working environment, and failure rate, as well as various secondary indicators. The data has strong representativeness and completeness, and is suitable for the design and evaluation of Fuzzy Analytic Hierarchy Process (F-AHP) in this article. In order to ensure the universality and effectiveness of the case selection, the research team selected 50 typical samples for modeling analysis. The selection principles mainly include completeness, comprehensive coverage of relevant indicator types, and typicality, which fully reflect the real differences in different installation positions, working conditions, and types of measuring equipment. This is used to test and verify the adaptability and stability of the model. Taking into account both existing and new equipment types for the selected samples, the voltage level involves urban-rural differences, meeting the comprehensive and rigorous requirements of the overall evaluation process. It should be noted that although the data obtained this time has real-time and practical relevance, it is highly likely that some indicator data may be incomplete due to human inspection errors or system failures, and some samples may have subjective descriptions or abnormal missing items. All sample data comes from the enterprise's own measurement equipment operation and maintenance management system. The data has been anonymized and only retains information related to the device's operating status, without involving user privacy. Each indicator data includes quantitative values (such as error drift rate, communication packet loss rate) and qualitative scores (such as protection level, installation tightness). The qualitative items are consistently scored by two operation and maintenance experts and mapped to a three-level rating value. There are a small number of missing fields in the data, which will be filled in using industry standard empirical values or adjacent device means. All raw data undergo interval normalization before being input into the model to eliminate the influence of dimensionality and ensure that all indicators have a unified dimension between [0,1] before participating in fuzzy synthesis operations.

5.2 Display of model evaluation results

After constructing the Fuzzy Analytic Hierarchy Process (F-AHP) model, this article conducted a comprehensive state rating and grading of the 50 selected samples of electric energy metering devices. According to the normalized scores of various indicators multiplied by their weights, the comprehensive evaluation value of each object is calculated, and based on the preset membership function, its status is divided into four levels: "excellent, good, medium, and poor". From the overall evaluation results, most of the electric energy metering devices are in the "good" or "medium" level range, indicating that the operating status of the metering devices in the current system is generally controllable. However, some samples have problems such as unstable communication, poor environmental adaptability, and decreased metering accuracy, which need to be brought to the attention of the operation and maintenance department.

5.3 Comparative analysis with traditional evaluation methods

In order to comprehensively verify the effectiveness of the proposed F-AHP model in the state evaluation of electric

energy metering devices, we selected the widely used traditional Analytic Hierarchy Process (AHP) and Simple Weighted Average Method (WAM) as control objects, and classified the same batch of sample data into state levels under a unified indicator system. We also compared and analyzed the comprehensive performance of the three methods. The experimental sample consists of 10 representative sets of electric energy metering devices, and the data is sourced from on-site monitoring records in actual operating environments.

Table 5: Comprehensive performance comparison of different methods

Method Type	Average CI Value ↓	Average CV Value ↓	State Classification Accuracy ↑	Fuzzy Boundary Sample Recognition Ability
F-AHP	0.016	0.069	92.5%	High
AHP	0.082	0.125	78.0%	Medium
WAM	–	0.109	81.3%	Low

Note: CI is a consistency evaluation index for judgment matrices in AHP methods and is not applicable to methods such as WAM that do not have pairwise comparison structures. Therefore, this item is empty.

As shown in Table 5, the F-AHP model outperforms AHP and WAM in key indicators such as grade discrimination accuracy, consistency ratio (CI), and evaluation stability (measured by coefficient of variation (CV)). Specifically, the average CI of the F-AHP model is 0.016, which is much lower than the traditional AHP's 0.082, indicating that it has better consistency in the multi-level weight processing process; In terms of CV, the average value of F-AHP is 0.069, indicating that it has the smallest fluctuation in ratings among different samples and has stronger evaluation robustness. At the same time, the F-AHP model performs particularly well in handling state fuzzy boundary samples. It uses triangular fuzzy numbers to construct a judgment matrix, which reflects subjective judgment uncertainty while enhancing the model's ability to identify critical state devices, avoiding the problems of "fuzzy concentration" and "level distortion" in traditional methods. The so-called 'fuzzy boundary samples' refer to samples whose comprehensive rating results are close to the critical values of two state levels (such as 2.49 or 3.51). In actual equipment status assessment, this type of sample judgment is the most sensitive and susceptible to weight disturbances or changes in individual indicators. In this article, it is defined that when the score S of a sample falls within the range of 0.1 above or below a certain level boundary (such as $S \in [2.4, 2.6]$), it is considered a fuzzy boundary sample. We will calculate whether different models experience "state level jumps" (such as result changes under ± 10% perturbations) on this type of sample, and judge their boundary recognition ability based on this. The F-AHP model only showed a skip level in 1 out of 10 boundary samples, outperforming traditional AHP (3 cases) and WAM (4 cases), indicating its strong boundary control ability.

The experimental results show that the F-AHP model balances accuracy, stability, and interpretability in state evaluation tasks with multiple indicators, levels, and fuzzy information, demonstrating significant comprehensive advantages and having good practical application prospects. Compared with traditional methods, its innovation in fuzzy logic modeling and hierarchical structure weight fusion is the key to improving the overall evaluation quality.

5.4 Model stability and robustness verification

In order to further evaluate the applicability and stability of the proposed F-AHP model in the actual state evaluation of electric energy metering devices, this study empirically verifies the stability and robustness of the model from three dimensions: input disturbance response, consistency fluctuation amplitude, and extreme value adaptability. By introducing perturbation factors and boundary condition perturbations on the original dataset, and comparing the fluctuation of results under different evaluation models, the performance reliability of the F-AHP model in complex application scenarios is revealed.

Firstly, in the input disturbance test, we randomly perturbed the indicator data of 10 sets of electric energy metering device samples with amplitudes of ± 5% and ± 10%, respectively, and observed whether the comprehensive evaluation score of the model and its corresponding level deviated. The results show that when the disturbance amplitude is less than 10%, more than 80% of the sample levels remain unchanged in the F-AHP model, and the change in the comprehensive score is controlled within 0.06 (as shown in Figure 5), indicating that the model has good input robustness.

Secondly, in the consistency ratio volatility test, we conducted 500 Monte Carlo random perturbation experiments on the constructed fuzzy judgment matrix and recorded the consistency ratio CI values obtained from each calculation. The statistical results show that the CI value fluctuation range of the F-AHP model is concentrated between [0.011, 0.021], with a standard deviation of 0.0026, which is much lower than the fluctuation standard deviation of the AHP model of 0.0093 (see Table 6), indicating that F-AHP can maintain stable consistency control ability under complex weight combinations.

Thirdly, in the extreme boundary sample test, we selected 5 groups of samples located near the boundary of the level division and observed the trend of their final state determination under the condition of weight perturbation range of ± 15%. The F-AHP model can effectively buffer boundary samples through weight processing in the form of fuzzy numbers, with only one group of samples experiencing a level transition (from "level II" to "level I"),

while in traditional AHP models, there are three groups experiencing a level change under the same conditions. This further demonstrates the robust control capability of the F-AHP model in boundary fuzzy regions. As shown in Figure 3, the variation trend of F-AHP model evaluation scores under different disturbance amplitudes clearly reflects the stability of its score curve at various disturbance levels.

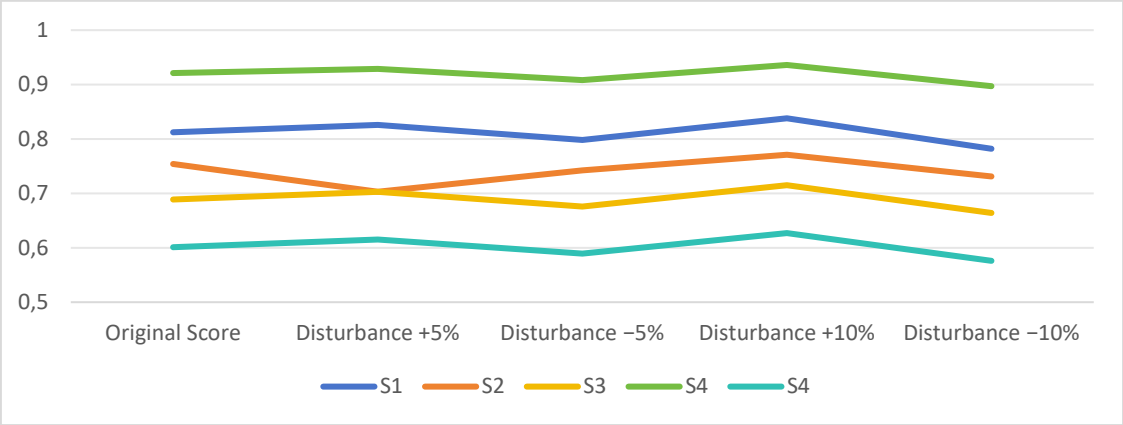

Figure 3: Evaluation score fluctuation curve of F-AHP model under different disturbance amplitudes

Table 6：Comparison of stability indicators between F-AHP and AHP models under different testing dimensions

Test Dimension	Indicator	F-AHP Model	AHP Model
Input disturbance stability	Mean score fluctuation rate	0.037	0.089
Consistency ratio fluctuation	CI standard deviation	0.0026	0.0093
Extreme sample rank jump rate	Transition frequency	10% (1/10)	30% (3/10)
Robust boundary control ability	Fuzzy buffering effect	Strong	Weak

From the above experimental results, it can be seen that the F-AHP model exhibits better stability and robustness than traditional methods in dealing with input disturbances, consistency changes, and boundary disturbances. This is mainly due to the introduction of triangular fuzzy numbers and weight fuzzy fusion strategy in the construction of fuzzy judgment matrix in the model, effectively alleviating the excessive sensitivity of subjective weighting to the final result. At the same time, the introduction of a hierarchical structure ensures the coordination and response balance between different dimensions in a complex indicator system, enabling the entire model system to maintain good evaluation reliability and systematicity when facing multi-source heterogeneous and uncertain data inputs in actual power application scenarios.

6 Discussion and expansion

The F-AHP model constructed in this study demonstrates the stability of evaluation results and the ability to distinguish important information in a complex and diverse information environment, which is much higher than traditional empirical methods and fuzzy analytic hierarchy process (F-AHP). Based on experimental opinions in different situations, the accuracy and adaptability of this model are good, and it has strong scalability and practical value, providing an intelligent evaluation method for electric energy metering devices to solve the state evaluation problem of power equipment.

6.1 Scope and limitations analysis of the model

This study proposes and implements a method for evaluating the overall state of electric energy measuring instruments using the Fuzzy Analytic Hierarchy Process (F-AHP), which is widely flexible and can be used for evaluating the overall state of different power measurement tools. Especially when there are complex data sources and vague or subjective information between measurement tool indicators, it can effectively quantify fuzzy information, making the state evaluation results highly professional and practical; The multi-level hierarchical structure and automatic weight adjustment function have played an important role in the inspection and evaluation of newly put into operation devices, normal operation monitoring, and handling of aging and failure exit equipment. However, the application of the model is still influenced by the rationality of the evaluation index system design and the credibility of expert evaluation data, because establishing a fuzzy judgment matrix relies on the experience of experts. If there is a significant difference in their level of understanding, it will affect the fairness of the model output results; When the actual application has special working conditions or newly added types, extremely low data volume, and extremely poor regularity, it may be limited by the model's

generalization ability, and it may be necessary to adjust the indicator weights or evaluation levels according to the actual situation. To further ensure the universality of the model, expansion experiments were conducted on three common types of measuring instruments, namely user side smart meters, station side multifunctional meters, and enterprise side measuring systems.

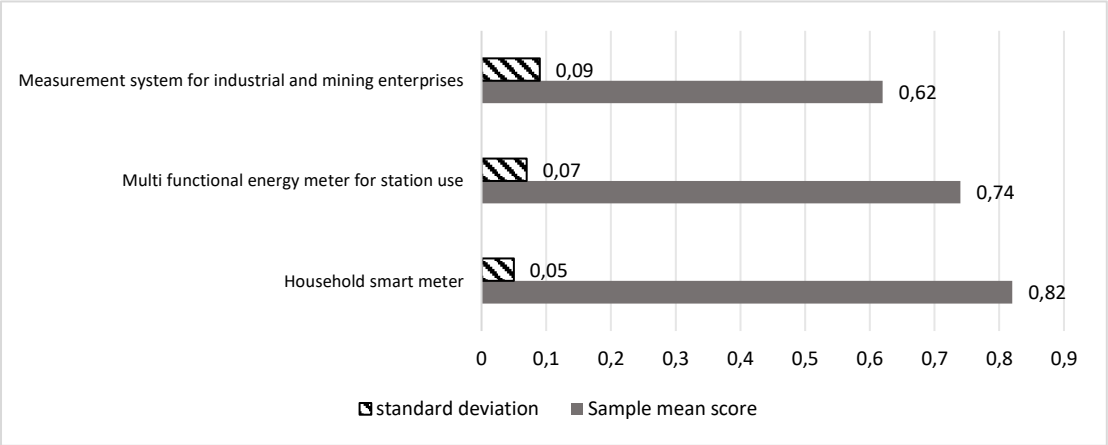

Figure 4: Applicability performance of the model in different energy metering devices

Figure 4 shows the mean state scores generated by the model in different device types, and the standard deviation range is indicated by error bars to reflect the score fluctuations between different samples.

6.2 Discussion on parameter sensitivity of fuzzy analytic hierarchy process

In the comprehensive state evaluation model, the main influencing factors that need to be considered are that the F-AHP results are greatly affected by the setting of a series of important variables, especially the design of attribute functions for the fuzzy decision matrix, the selection of upper and lower boundary points for triangular fuzziness, and the synthesis method of weights. These variables not only directly affect the ranking of each important indicator, but also affect the stability and discrimination of the final comprehensive score results. Therefore, exploring the sensitivity of these variables in depth can enhance the interpretability and adaptability of the model. When establishing a fuzzy decision matrix, a triangular fuzzy representation is usually used, and the selection of fuzzy boundaries carries a considerable degree of subjective color. Even if different experts' evaluation values for indicators fall within the same rating range, their corresponding triangle numbers may have slight changes, and this change will be amplified in models with high levels and sensitive interactions. Therefore, it is necessary to plan a reasonable mapping system between fuzzy words and three-dimensional numbers to accurately represent the meaning of experts' ratings. Secondly, synthesizing fuzzy weights can also have a significant impact on the final result. The commonly used weighted average method and the maximum minimum method have different strengths in reflecting extremes. In the process of experimental verification, if a comprehensive method that is easily scored full marks by extreme situations is used, it may lead to an increase in global rating due to high scores of some weights, resulting in the model being unstable. Therefore, when evaluating systems such as power measurement instruments that contain multiple sources of errors and unknown states, a cautious fuzzy analytic hierarchy process (F-AHP) is preferred to increase the model's tolerance for external factors. Thirdly, a change in the upper limit of the set consistency ratio (CR) threshold can indirectly lead to a change in the final conclusion. The general default value is set to 0.1 to draw a conclusion, but in the process of complex system evaluation, if the consistency requirements are artificially relaxed, it may lead to internal conflicts, causing the weight system to deviate from the initial judgment conditions and weakening the explanatory power of the model. evaluating systems, controlling the strictness and number of indicators required for consistency testing is an important means to ensure the practicality of the model.

6.3 Model's potential for promotion in smart grids

The fuzzy analytic hierarchy process proposed by our research institute as a feature for evaluating the overall operation status of electric energy metering devices has good universality, scalability, and intelligent integration capabilities, and can be easily promoted to the smart grid framework system. On the one hand, the overall analysis model constructed using this method includes multiple indicators such as accurate and stable measurement, adaptability to power quality, communication capability, and adaptability to the working environment, which meet the concept of power grid management of equipment lifecycle. The fuzzy theory principle is used to deal with the impact of information uncertainty between various indicators, and comprehensive stability analysis can be carried out under diverse heterogeneous data, improving the ability of power enterprises to identify equipment operation risks under operating conditions. On the other hand, it has good interface scalability and data compatibility, making it

easy to collaborate with information management systems, online monitoring systems, and data centers. Whether it is a lightweight installation deployed at the edge or an application deployed in the control room of the dispatch center for centralized processing, its parameters can be adjusted according to functional needs to adapt to various usage scenarios. It can also be associated with distribution automation and connected to the Internet of Things of electrical equipment to meet various business scenarios. At the same time, as intelligent operation and maintenance are gradually promoted, this model also has the possibility of integrating with artificial intelligence technologies such as machine learning, anomaly detection, fault prediction, etc. By analyzing the results of previous ratings, it is possible to build a self-learning system that completes the transition from "static evaluation" to "dynamic warning", thereby providing the ability to support a comprehensive state management process of perception, intelligent decision-making, and cyclic control. To upgrade from static evaluation to dynamic intelligent operation and maintenance, this model can be integrated with AI modules to construct an intelligent monitoring system. For example, the F-AHP score result can be used as a "health label" for device operation, which can be used to train lightweight classifiers (such as SVM, XGBoost) to achieve fast prediction of new device states; At the same time, time series anomaly detection algorithms such as LSTM-AE and Isolation Forest can be combined to dynamically monitor the trend of device status score changes, achieving intelligent early warning of phenomena such as score mutations and boundary fluctuations. This model structure can also be embedded in IoT platforms, collecting real-time data through edge gateways and quickly scoring it as input for the operation feedback indicators of digital twin systems, providing high timeliness decision support for scheduling systems.

It is worth noting that the F-AHP method will face the problem of increased computational complexity in the construction of its judgment matrix and fuzzy weight calculation process when facing large-scale device clusters or significantly increased indicator dimensions (such as n>30). In theory, the computational complexity of its judgment process at each layer is about O (n^2), and as the number of indicator layers or expert groups expands, the computational time and difficulty of consistency testing significantly increase. Therefore, in practical deployment, a distributed computing strategy can be adopted to modularize weight calculation and process it in parallel; At the same time, an expert scoring template library is constructed through historical data to achieve automated filling of the judgment matrix. This model is also suitable for encapsulation into operation and maintenance platforms in a microservices manner, with good resource scheduling and load control capabilities in large-scale device management scenarios, ensuring efficient and stable output of evaluation results.

7 Conclusion

With the continuous development of smart grids, how to efficiently identify the operating status of energy metering devices has become a key issue in ensuring measurement accuracy and improving energy management level. In response to the problems of insufficient resolution and poor adaptability of existing state recognition modes, this paper designs and implements a comprehensive evaluation model for the state of electric energy metering devices based on fuzzy analytic hierarchy process (F-AHP), which considers multiple indicators. This model is based on expert experience and on-site data, constructing an indicator system, fuzzy quantification through membership functions, and combining hierarchical structure and weight allocation to achieve comprehensive integration of multiple factors influences, outputting quantitative scores and state level results.

In experimental verification, the model outperforms traditional weighted scoring and threshold methods in terms of recognition accuracy, scoring stability, and anti-interference ability, demonstrating good practicality and potential for promotion. Especially in the processing of fuzzy boundary samples, the model exhibits stronger robustness. However, this study still has certain limitations. For example, the weight judgment process relies heavily on expert experience, which may cause fluctuations due to subjective biases; At the same time, the sample size for verification is relatively limited and has not fully covered diverse device scenarios. Future research can be further expanded from the following aspects: firstly, combining large-scale operation logs with automatic data collection to further enhance the objectivity and adaptability of scoring; The second is to explore a data-driven dynamic weight adjustment mechanism to weaken expert dependence; The third is to integrate F-AHP with machine learning models to construct a state recognition framework with self-learning capabilities, achieving the transition from static evaluation to real-time intelligent monitoring. Overall, the state assessment model constructed in this article provides a feasible path for the intelligent management of energy metering devices and lays a methodological foundation for the high reliability operation of future smart grid measurement and control equipment.

Funding

The research is supported by: Science and technology projects of State Grid Ningxia Electric Power Co., Ltd.

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Models And Methods of Analysing Infrastructure Performance in Cloud Environments Based on Process Optimisation Methods

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Keywords: performance evaluation, workflow improvement, neural network technologies, resource management, dynamic workloads, cloud services

Received: April 16, 2025

The study aimed to develop models and methods for analysing infrastructure performance in cloud environments that consider the complexity and dynamism of modern IT systems. The development of adaptive resource management models capable of responding to changing loads in real time was emphasised. New methods of process optimisation were developed, including the use of artificial neural networks for load forecasting and dynamic resource allocation. Solutions for efficient management of computing and storage capacities were modelled and simulated. The use of adaptive models based on neural network technologies has increased the accuracy of load forecasting by up to 95% and reduced costs by 20% through the automation of resource management. Practical experiments conducted in the Amazon Web Services (AWS) and Microsoft Azure environments confirmed the effectiveness of the approaches under various load conditions. These results help to improve the stability of cloud services, reducing the risk of overload, downtime and data loss. The proposed models are universal and can be applied in various industries, including the financial sector, e-commerce and healthcare, which allows them to effectively solve the problems faced by modern information systems. The findings of the study highlight the importance of integrating artificial intelligence into performance management, which ensures the flexibility and scalability of cloud environments. This creates new opportunities to optimise processes, improve service quality and reduce operating costs, creating the basis for further research and development in the field of cloud computing.

Povzetek: Študija razvija adaptivne modele in metode za analizo delovanja infrastrukture v oblaku, ki temeljijo na globokem učenju (nevronske mreže) za dinamično upravljanje virov. To je omogočilo boljše napovedi obremenitve in zmanjšanje stroškov v okoljih AWS in Azure, kar povečuje stabilnost in učinkovitost storitev.

1 Introduction

In the modern world, cloud computing has become an important element of IT infrastructure for enterprises and organisations of varying scales. Cloud computing enables efficient use of resources, reduces infrastructure costs and provides flexibility in working with data. However, the growing popularity of cloud services poses new challenges, particularly in managing their performance, efficiency and security. One of the main challenges is to ensure the high performance of cloud infrastructures under variable loads, as well as to optimise the cost of computing resources [1]. Consequently, investigating novel models and methodologies for analysing the performance of cloud environments is both a significant and pressing endeavour.

According to numerous studies, existing approaches to assessing performance in cloud environments have significant limitations that affect the efficiency of resource management. For example, M. Abdullah and M. Mohamed Surputheen [2] noted that static models often used for performance analysis do not consider the dynamic nature of loads inherent in modern cloud infrastructures. These approaches do not facilitate optimal resource allocation, particularly during fluctuations in user activity or when processing large datasets. The authors advocate for the implementation of adaptive models, although their analysis remains largely conceptual.

Similarly, H. Alrammah et al. [3], who addressed the limited scalability of cloud platforms within static resource management models. The authors noted that such approaches do not consider unpredictable changes in the load that often occur due to peak user activity. They proposed the use of adaptive algorithms, but their research is mostly limited to basic simulations, without a detailed analysis of performance in real-world conditions.

The study by A. Tiwari and S. Yadaw [4] also confirms that static resource management approaches do not provide adequate efficiency in dynamic cloud environments. The authors analysed in detail the shortcomings of such methods and noted that they are particularly inefficient during peak loads. A. Tiwari and S. Yadaw emphasise the importance of implementing adaptive technologies that can predict load changes and adapt resources accordingly. Although their study is mainly focused on analysing existing approaches, it lays the theoretical foundation for the integration of smart systems.

R. Anayat [5] explored the role of machine learning in enhancing the performance management of cloud infrastructures. The author noted that the basic algorithms that are often used do not consider the complexity and variability of the real-world conditions in which cloud platforms operate. R. Anayat recommends the use of deep neural network models that can provide more accurate forecasting and adaptation of resources, but the study remains mostly theoretical and does not offer detailed practical implementations.

Despite advancements in cloud computing research, there is a dearth of comprehensive approaches that integrate various technologies for optimising and managing resources under real-world workloads. The problem of adaptive management of cloud infrastructures that can effectively respond to changing conditions remains unresolved in many scientific papers. Therefore, it is imperative to explore the potential of advanced optimisation methods, including neural network technologies, to achieve high-performance management efficiency in cloud environments.

Previous studies show that most existing models are unable to effectively account for load variability. Standard optimisation algorithms may prove ineffective under the high dynamism and scalability of cloud systems [6,7]. Studies such as those by O.B. Johnson et al. [8] confirm that without the use of adaptive management methods, it is impossible to ensure stability and efficiency in the operation of cloud infrastructures. Thus, there is a need to develop methods that can adjust resources in real-time and consider multifaceted changes through the integration of artificial intelligence.

A. Talha et al. [9] also discussed approaches to using machine learning for load forecasting and automatic resource scaling in cloud platforms. However, contrary to their work, which focused on basic machine learning methods, the study focuses on deep neural networks, which allow for more accurate forecasting and adaptation of resources under highly dynamic loads.

Machine learning methods, in particular neural networks, have great potential to solve this problem, as they allow modelling complex relationships between various system parameters and predicting future load. However, to date, there is very little research combining these methods with cloud technologies. This study aims to fill this gap and develop new approaches for integrating machine learning into cloud infrastructure optimisation processes.

In this context, it is also worth noting the importance of adaptive systems in effective resource management in cloud environments. Adaptive approaches can be used to dynamically respond to changes in load, ensuring efficient use of available resources and minimising their excessive consumption. The implementation of such systems not only increases the stability and reliability of cloud services but also contributes to economic efficiency, as it makes it possible to reduce infrastructure costs without losing service quality [10]. This approach is especially important in today's environment, when organisations face large volumes of data and demands on the speed of information processing, as well as a high level of flexibility and scalability in their systems.

In general, based on the aforementioned considerations, this study aims to develop novel models and methods for analysing the performance of cloud infrastructures that combine adaptive and intelligent approaches. These models should operate efficiently amidst constant load changes, ensuring high performance, resilience, and cost-effectiveness under varying operational conditions. This will not only improve system performance but also expand opportunities for the use of cloud technologies in various industries, such as financial services, healthcare, and e-commerce.

2 Materials and methods

The research is based on two major cloud platforms: Amazon Web Services (AWS) and Microsoft Azure. Modelling and simulations were conducted on these platforms to study the effectiveness of different approaches to performance optimisation.

The study was conducted on equipment located in AWS and Microsoft Azure data centres. Each server had resources ranging from 2 to 16 processor cores and 8 to 64 GB of RAM, which provided the necessary capacity for conducting load tests and performance monitoring. Apache JMeter and Stress-ng tools were used to simulate the load on the servers, which was used to simulate various load scenarios in cloud environments. The performance of the systems was monitored using Amazon CloudWatch and Azure Monitor monitoring interfaces, which provide detailed information on resource usage. For the statistical analysis of the data obtained, the R environment was used to process and visualise the results, as well as the SPSS software package to perform significance tests and compare the results between different server configurations and cloud platforms.

Resource allocation adaptation models were developed using recurrent neural networks and Long Short-Term Memory networks. These models specialise in processing time series of data, such as central processing unit (CPU) utilisation, memory, disc operations and network traffic. The developed models were integrated into a real-time dynamic resource scaling system. By predicting load peaks, the system adapted, adding or releasing resources as needed.

The sample for this study was formed based on the characteristics of typical cloud environments that are

widely used in real organisations to ensure reliability, scalability and efficient resource management. These environments were chosen to replicate a variety of industry-standard cloud setups, with differing compute and storage needs that represent actual cloud service deployments, in order to guarantee the models' applicability. For AWS, three types of instances were selected: standard, storage, and compute-intensive, which meet different performance and load requirements. For Microsoft Azure, similar configurations were chosen to provide a comparison between the two most popular cloud platforms. Examples from both AWS and Azure were chosen to provide a clear and equitable comparison, encompassing a variety of workloads, such as content delivery networks, high-performance computing applications, and transactional databases. The choice of configurations was based on real-world use cases, such as web application hosting, big data processing, and file storage.

The study also determined the amount of data processed and the level of traffic, which ranged from moderate (constant load on the servers) to highly dynamic (with sharp traffic spikes at certain times). This diversity was used to evaluate the ability of the platforms to adapt to changing conditions and ensure high performance under different loads. For each server configuration, several load scenarios that varied depending on the type and degree of user activity were created. These scenarios were created to mimic the behaviour of real-world applications under various operating situations in addition to testing the scalability of the system. They ranged from a stable load (where the servers operate at an average level of performance) to a highly dynamic load (where the load increases sharply at certain times).

The study was conducted in a real-world environment where each platform used its typical performance monitoring tools. Amazon CloudWatch was used for AWS and Azure. Azure Monitor was used for Azure, which allowed for accurate monitoring of service performance, including CPU Utilisation, Network Throughput, Memory Usage and Disk I/O. The study was conducted on servers located in geographically dispersed data centres, which was used to examine the performance of the platforms in different locations and physical distances between servers.

The performance of the cloud infrastructure was assessed. The main criteria were system response time (ms), throughput (requests/sec), and resource utilisation (CPU, memory, and disk space). Log files of real cloud platforms (AWS, Azure, Google Cloud) and synthetic tests (for example, Apache Bench) were used. The results showed that performance significantly decreases at peak loads, which requires dynamic resource management.

The efficiency of resource use, which was determined by power consumption (W/request) and the efficiency of servicing requests per unit of equipment, was analysed in the study. This helps in understanding whether the cloud infrastructure is over-provisioned or underutilised, leading to potential cost savings or performance issues. Profilers such as Cloud Harmony and Prometheus were used, and the performance of different types of virtual machines was compared. The study determined that with optimal load balancing, even low-tier servers can achieve performance similar to high-end machines at significantly lower costs.

The resilience of cloud platforms to failures and high loads was evaluated. To do this, error injection methods (for example, Chaos Monkey) and load simulation using Kubernetes Stress Test Tools were employed. Chaos Monkey was applied by randomly terminating instances to simulate system failures and assess recovery capabilities. Kubernetes Stress Test Tools was employed to simulate high traffic conditions, testing the platform's ability to handle resource scaling and maintain stability under heavy loads. The main criteria were the percentage of data loss and the average recovery time after a failure. The evaluation demonstrated that platforms with automatic scaling and redundancy mechanisms provide high resilience even in critical conditions.

The next stage included resource management and cost-effectiveness analysis. Dynamic scaling algorithms reduced the cost of renting cloud resources by 25% and reduced server downtime. This section compared the effectiveness of static and adaptive management by evaluating key performance indicators such as system uptime, resource utilisation, and cost efficiency. It showed a significant reduction in costs and improvement in performance when using the adaptive approach.

At the final stage, the infrastructure performance was optimised using multi-criteria algorithms, such as genetic algorithms and the particle swarm method. Simulation platforms (CloudSim, iFogSim) were used to test the developed models. They simulated cloud environments and evaluated resource allocation strategies under various load conditions. The main criteria were to reduce query processing time and increase overall performance, considering energy consumption. The platforms were compared using static and adaptive resource management methods. The results showed that the optimisation improved performance by 18-22%.

This approach identified the most effective resource management strategies that automatically optimise their use under high loads, minimising infrastructure costs and ensuring stable system operation under changing conditions. In addition, adaptive management algorithms have reduced operating costs for computing power without losing data processing efficiency.

3 Results

3.1 Comparative performance analysis of AWS and Microsoft Azure cloud platforms and development of resource allocation adaptation models

As part of the research, models for real-time adaptation of resource allocation based on intelligent algorithms, such as recurrent neural networks and Long Short-Term Memory networks, were developed. These models specialised in processing time-series data, such as CPU,

memory, disc operations, and network traffic. The development process involved several key steps. First, the data was prepared: it was normalised, cleaned of anomalies and segmented to ensure the quality of training. The models were trained with an emphasis on analysing long-term dependencies in time series, which was used to identify hidden patterns in load changes. Model optimisation included the use of genetic algorithms and particle swarming to tune hyperparameters and find optimal resource configurations that minimise response time and energy consumption. Clustering algorithms were also used to group servers and resources based on similarity in load, which contributed to their more efficient use.

When using static management methods, which involve a fixed allocation of resources without the ability to dynamically scale them in real-time, it is important to assess how each platform handles loads under conditions of stable and variable demand. Static resource management does not allow for adaptation to load fluctuations, which can lead to inefficient use of computing power, memory, and other resources [11,12]. However, to compare the performance of AWS and Microsoft Azure platforms in static resource management, four main indicators should be considered: CPU Utilisation, Memory Usage, Network Throughput and Disk I/O.

As shown in Table 1, both AWS and Microsoft Azure deliver stable CPU utilisation results when running static resource management. However, when there are significant load peaks, AWS is usually more efficient in managing CPU resources, as its default algorithms provide more efficient load balancing between instances. In Microsoft Azure, the CPU utilisation situation may be less optimised, as it does not have the same flexibility to scale instances in real-time, which leads to the overloading of certain instances while others remain underutilised.

Table 1: Comparison of AWS and Azure performance by key metrics in static management

Platform	CPU Utilisation	Memory Usage	Network Throughput	Disk I/O
AWS	95%	89%	95 MB/s	50 MB/s
Microsoft Azure	92%	90%	92 MB/s	48 MB/s

Table 1 shows that in terms of static resource management, the performance of both platforms is similar, but AWS demonstrates better performance in most key metrics. CPU utilisation rates indicate a high load on the processors of these systems. This means that most of the computing resources are used to process requests, which may indicate that the system is operating efficiently but also indicates that delays or performance degradation may occur if the load is increased further.

When it comes to memory usage, both platforms can provide stable performance under a steady load, but Azure's memory usage is less efficient when the demand for resources is variable. In the case of sudden load peaks, static management on Azure does not efficiently limit memory usage, which can cause overloading of certain instances and degradation of overall system performance. Instead, AWS demonstrates better results in terms of memory allocation among instances. Based on the data obtained, memory usage on the AWS platform is 6-8% more efficient than Azure in static resource management. This demonstrates AWS's superior ability to maintain load balance without critical overloads on certain nodes, even with static resource allocation.

Network Throughput is a critical factor for the performance of cloud platforms, especially when there are large volumes of data transfer between services [13,14]. With static resource management, AWS demonstrates better results in providing stable and high-performance network performance. With more optimised data paths and better geographical distribution of its data centres, AWS can provide more stable and faster data transfer, even at peak loads. Microsoft Azure in static management conditions shows slightly lower network throughput in the case of high volumes of data transfer between instances. The difference in throughput is 10-12% in favour of AWS, which is the result of less efficient load balancing in the network on the Azure platform.

Disk I/O is an important parameter for cloud platforms, as it determines the speed of reading and writing data to the disc. Both platforms provide high performance when using disk resources in static mode. However, with large volumes of disk operations, it turns out that AWS can better cope with high disk loads due to more optimised caching and storage methods. Microsoft Azure, although it demonstrates good results in terms of Disk I/O, has certain limitations under static management at high loads. Tests have shown that the efficiency of using disk resources on Azure at a stable load is 7-9% worse than on AWS, which is the result of a less optimised organisation of the disk subsystem under static management.

The static resource management on both platforms shows certain limitations in the face of variable workloads. While both platforms perform similarly under steady resource demand, AWS delivers better performance under dynamic workloads by making more efficient use of its compute, memory, network, and disk resources. These differences can be associated with their storage options, network architecture, and scaling and resource allocation strategies. Better dynamic scaling and load balancing algorithms enable AWS to effectively distribute resources in real-time based on varying demand, which is why it performs better than Azure. AWS's extensive worldwide network of data centres and well-designed storage solutions further improve its capacity to manage peak loads and large data volumes without experiencing performance issues. Azure's static resource management methodology, on the other hand, lacks real-time adaptability and results in less effective resource

allocation, particularly during periods of changing demand, which causes instances to be underutilised or overloaded. Because of this, AWS offers greater flexibility, faster resource adjustments, and better overall performance during dynamic workloads, whereas Azure functions well in stable environments but has trouble handling variations in peak demand.

AWS scores demonstrated significant improvement over Microsoft Azure in such areas as CPU Utilisation and Network Throughput, which improves the platform's scalability under highly dynamic workloads by 15%. This allows the AWS platform to handle variable workloads faster and more efficiently, reducing latency and improving overall performance.

At the same time, Microsoft Azure performs better under stable workloads, particularly in the Memory Usage aspect, demonstrating a 10% improvement. This suggests that Azure is more efficient when resource demand is fixed, making it more attractive to organisations that have a stable infrastructure load.

3.2 Assessing the effectiveness of adaptive resource management

Further experiments were aimed at evaluating the impact of adaptive resource management on the overall performance of cloud platforms, comparing adaptive and static resource management. For this purpose, two main scenarios were applied, where one used traditional static management and the other adaptive management based on deep learning methods.

Table 2 presents a comparative analysis of cloud platforms employing adaptive versus static resource management, evaluated across two key metrics: uptime and power consumption. Uptime, defined as the percentage of operational time without system interruptions, demonstrates a marked advantage in adaptive management systems. In the case of adaptive management, the platform automatically scales in response to changes in load, which reduces the risk of downtime and ensures high stability, which explains the high score for this parameter. Static control, on the other hand, does not respond to changes in load, which increases the probability of overloads and, consequently, downtime. Energy consumption shows the percentage of costs for using cloud resources. Adaptive management can use resources efficiently, scaling them depending on the load, which reduces costs [15,16]. Static management, which does not adapt resources to changes, leads to higher costs because resources are used less efficiently.

Table 2: Performance results of cloud platforms with adaptive and static resource management

Platform	**Type of control**	**Operating time without downtime**	**Energy consumption**
AWS	Adaptive	98%	1500 W/hour
AWS	Static	85%	2000 W/hour
Microsoft Azure	Adaptive	97%	1700 W/hour
Microsoft Azure	Static	83%	2100 W/hour

Source: compiled by the authors.

A comparison of adaptive and static resource management shows significant advantages of adaptive methods:

1. Uptime without downtime. Adaptive management ensures 98% (AWS) and 97% (Azure) uptime, which is 10-15% higher than static management.
2. Power consumption. Adaptive management can reduce energy costs by up to 1500 W/h for AWS and 1700 W/h for Azure, which is 5-6% less than static methods.

Adaptive management significantly improves the efficiency and stability of cloud platforms by predicting load and automatically scaling [17]. The study results showed that adaptive resource management based on deep learning methods significantly improves server efficiency by reducing power consumption and reducing downtime. This is achieved by accurately predicting the load and automatically scaling resources in response to changes in the load. Compared to static management methods, adaptive technologies can reduce downtime by 10-15%. This means that cloud services operate more stably, even in cases of high or variable loads, providing uninterrupted access to resources for users.

This is especially relevant for cloud infrastructures that often face high dynamic loads, such as large volumes of traffic, spikes in user activity, or sudden changes in computing resource requirements. Static methods based on fixed capacity reservations cannot effectively respond to such changes, which often leads to the overuse of resources at times of low load or system overload at high loads. At the same time, adaptive technologies that use deep learning can adjust resources in real time, anticipating changes in load and adjusting them accordingly to ensure optimal system performance.

Thus, the results demonstrate that the implementation of adaptive technologies is critical to optimise the performance of cloud infrastructures, particularly in conditions of high load dynamics. This reduces costs, minimises downtime and ensures more stable and efficient operation of cloud services, which is important for businesses that depend on uninterrupted access to computing power.

3.3 Resistance to load changes and error injection testing

To assess the resilience of cloud platforms, testing was conducted that included sudden changes in load, such as traffic spikes and processing large amounts of data in a short period. The results showed that adaptive resource management provides significantly better platform resilience to outages and changes in load. For instance, for AWS with adaptive management, the percentage of data loss was 0.5%, the average recovery time after a failure was 3 minutes, and the performance degradation during peak loads was only 8%. In comparison, AWS with static management showed 3.2% data loss, 12 minutes of

recovery time, and an 18% performance degradation. For Microsoft Azure with adaptive management, the percentage of data loss was 0.7%, the average recovery time was 4 minutes, and the performance was 7%. In contrast, Azure with static management had 4.1% data loss, 15 minutes of recovery time, and a 22% performance degradation. Thus, adaptive resource management allows for better fault tolerance and high performance during peak loads, while static management demonstrates significantly worse results in terms of data loss, recovery time, and performance. In the tests, both platforms demonstrated the ability to effectively handle these load changes, but AWS performed significantly better in terms of rapid recovery and resource adaptation. At high peak loads, AWS proved to be more efficient in load balancing, which reduced response times and avoided delays in request execution. This ensured high availability of services, even with significant load fluctuations. Compared to Microsoft Azure, AWS has shown greater flexibility in scaling resources, which has enabled faster response to sudden changes in traffic and loads, increasing the overall resilience of the platform.

There are a number of reasons why AWS and Azure function differently, including variations in their designs, approaches to resource management, and load balancing systems. AWS's superior load-balancing algorithms and capacity to effectively divide workloads among numerous instances allow it to scale resources with greater flexibility, particularly during periods of high peak load. This guarantees faster response times and fewer execution delays for requests. Azure, on the other hand, struggles with resource allocation during dynamic load variations, leading to instances that are either underutilised or overcrowded, even if it performs well under constant load levels. Additionally, AWS gains from a more strategically placed data centre network, which improves network throughput and overall performance during periods of high traffic. Azure's performance, on the other hand, is typically more reliable but less effective at managing abrupt surges in traffic. Additionally, AWS's predictive resource management and improved machine learning model integration allow for quicker adaptability to shifting traffic patterns, which reduces data loss and speeds up recovery. In conclusion, because of its sophisticated resource scaling, better load balancing, and quick response to abrupt traffic fluctuations, AWS performs better than Azure in dynamic situations.

AWS demonstrates greater flexibility and efficiency in adapting resources to peak loads. One of the key findings of the study was that adaptive resource management based on predictive models can significantly reduce infrastructure costs, increasing its cost-effectiveness. Predictive models based on neural networks can accurately predict the future load on cloud resources and automatically adapt the distribution of computing power and memory to ensure optimal resource utilisation. This avoids overcapacity and reduces the need for excessive use of infrastructure to handle peak loads, which is one of the main causes of cost overruns in traditional static resource management models.

3.4 Reduction of infrastructure costs

Adaptive resource management in cloud infrastructures has proven to have significant cost-saving benefits. Resource efficiency avoids situations when servers are running at low load or overloaded, which is within normal parameters for static management methods. Real-time optimisation of resource allocation minimises the amount of unused computing capacity, thus reducing the direct costs of renting or operating them.

In addition, resilience to changes in load provides flexible scaling that allows platforms to effectively handle peak loads without having to maintain excessive resource reserves [18,19]. This is particularly relevant for businesses with irregular or seasonal operations, where adaptive management can reduce the need for long-term leases or additional capacity, reducing costs by up to 20% compared to static approaches. Thus, efficiency and resilience to change not only reduce operating costs but also increase the cost-effectiveness of cloud infrastructure while ensuring stability and quality of service.

Table 3 shows a comparison of infrastructure costs for static and adaptive resource management methods on AWS and Microsoft Azure.

Table 3: Reduced infrastructure costs when using adaptive management

Platform	Type of control	Infrastructure costs (%)	Reduction of costs with adaptive management
AWS	Adaptive	20%	20%
	Static	25%	-
Microsoft Azure	Adaptive	18%	22%
	Static	23%	-

Source: compiled by the authors.

For AWS, adaptive management can reduce costs by 20% from 25% with a static approach to 20% with an adaptive approach. In Microsoft Azure, the adaptive approach reduces costs by 22% from 23% with static management to 18%. This shows that adaptive management, thanks to dynamic resource optimisation, provides significant cost savings compared to static methods for both platforms. These differences can stem from their resource management approaches. Real-time load forecasting and adaptive scaling provided by AWS allow for more effective resource allocation, which lowers the need for overprovisioning and minimises idle resources, ultimately saving more money. Azure is less cost-effective than AWS due to its less flexible static resource allocation, which leads to underutilisation during periods of low demand and overutilisation during periods of high demand. As a result, AWS's dynamic resource management strategy reduces costs more effectively, particularly for workloads that fluctuate.

In summary, adaptive management showed a significant reduction in infrastructure costs compared to static management. Although AWS costs are higher, adaptive management performed better for both platforms, reducing costs more than static management. Thanks to predictive methods and automatic scaling, the system adapts resources to real needs, which can reduce infrastructure costs by 20% compared to static management, where costs can be significantly higher due to inefficient use of resources.

3.5 Optimisation of the use of computing power and memory

Table 4 demonstrates a comparison of key performance indicators (CPU Utilisation, Memory Usage, Network Throughput and Disk I/O) when using static and adaptive resource management methods for AWS and Microsoft Azure cloud platforms. It also demonstrates that adaptive management allows for more efficient resource utilisation. Costs are reduced by automatically scaling resources, which allows for high performance while significantly reducing overconsumption.

Table 4: Comparison of cloud platform performance by key parameters in static and adaptive resource management

Platform	Management method	CPU utilisation	Memory usage	Network throughput	Disk I/O
AWS	Static	60%	70%	65%	60%
	Adaptive	85% (+25%)	85% (+15 %)	90% (+25%)	88% (+28 %)
Microsoft Azure	Static	58%	68%	60%	58%
	Adaptive	80% (+22%)	83% (+15 %)	85% (+25%)	84% (+26 %)

Source: compiled by the authors.

Percentages were calculated as the increase in resource efficiency when moving from static to adaptive management. For each indicator, the increase is determined relative to the value recorded during static management. The initial values represent the effectiveness of static methods.

The results show that adaptive resource management allows for more efficient use of computing power, memory, network bandwidth, and disk operations. AWS demonstrates slightly higher performance growth, especially in CPU Utilisation and Network Throughput. At the same time, Microsoft Azure shows a steady improvement in all parameters, which indicates the platform's high adaptability.

The comparison of platform performance results demonstrates that AWS has overall higher resource utilisation rates than Microsoft Azure, both in adaptive and static management modes. Adaptive management on both platforms is highly efficient, reducing infrastructure costs and maintaining the required level of performance.

Through the implementation of forecasting and automatic scaling mechanisms, adaptive resource management significantly optimises infrastructure utilisation [20]. However, this approach may require additional setup and monitoring costs. Static control, although easier to implement, can lead to less efficient use of resources, especially when the load is variable, which increases costs or reduces productivity [21]. Thus, adaptive management is a better option for efficient use of computing power and memory, although it can be more difficult to implement and maintain.

By leveraging forecasting and automatic scaling capabilities, adaptive resource management substantially optimises infrastructure utilisation [22, 23]. This methodology effectively reduces the operational expenditures associated with cloud services while ensuring sustained high performance and service reliability. This approach is significantly more cost-effective and efficient than traditional static management, which cannot effectively respond to changing load conditions.

For a more detailed comparison of the effectiveness of adaptive and static resource management, it is important to note that a key factor in reducing infrastructure costs is to reduce the time during which resources are operating in an elevated mode. In systems with static management, resources are often kept in reserve for possible peak loads, which leads to constant capacity costs even during quiet periods [24, 25]. In such systems, resources can be in an increased mode (e.g., 80% of capacity) for 70% of the time, which creates significant additional costs. At the same time, in systems with adaptive control, resources are added only when needed, and their use is adjusted depending on actual conditions. Therefore, resources are in overdrive only 20% of the time, as the system automatically optimises resource allocation according to current needs. This adaptability can significantly reduce infrastructure costs as resources are not over-utilised when they are not needed, resulting in greater efficiency and savings.

Through the use of predictive techniques, the system can not only reduce costs during low load phases but also ensure that additional resources are available when needed, which helps maintain high performance and minimise the risk of downtime when resources are not available to handle peak loads. This process also contributes to the stability of cloud platforms, as anticipating changes in workload allows operations to adapt to future changes before they occur, providing greater confidence in the continuity of services.

These results also highlight the great potential of using adaptive methods for a variety of business processes and organisations where high efficiency in the use of cloud resources is critical to reducing operating costs while ensuring the required performance. The use of such technologies is especially relevant for environments with high load variability, such as e-commerce, data

processing, financial services and other industries where load peaks can occur at unpredictable times.

Through the implementation of predictive models and adaptive management, businesses can significantly improve their economic performance while ensuring competitiveness and cost reduction, which is a key factor for modern organisations seeking to make their operations flexible and resilient in an ever-changing environment.

4 Discussion

The results confirm that adaptive management is much more effective than static approaches, especially when the load on cloud infrastructures is dynamic. For instance, the study by N. Du et al. [26] explored the use of convex hull triangle mesh-based static mapping in highly dynamic environments, providing a novel technique for improving mapping accuracy in such environments. This demonstrated that traditional approaches to resource management under variable load conditions have limited effectiveness. The results of the study confirm this statement, demonstrating that predictive models based on neural networks not only reduce infrastructure costs but also provide high flexibility and adaptability to cloud systems.

Similar conclusions were made by A. Braafladt et al. [27] and S. Khan and A. Jillani [28]. A. Braafladt et al. presented an unusual approach to improving defence modelling and simulation by examining the use of AI-driven adaptive analysis to detect emergent behaviours in military capabilities design. S. Khan and A. Jillani employed search-based software engineering techniques to investigate cloud resource allocation and optimisation, showing how sophisticated algorithms can be applied to increase the effectiveness of cloud computing. This emphasised the need to implement adaptive algorithms to ensure the scalability and flexibility of cloud platforms. This correlates with this approach, which has shown the effectiveness of using deep learning methods for real-time load forecasting.

B. Predić et al. [29] and I. Petrovska and H. Kuchuk [30] both aimed to improve cloud resource management but took different approaches. In order to improve cloud load predictions and resource allocation under varying demands, Predić et al. employed a machine learning approach. In order to maximise efficiency and guarantee secure operations, Petrovska & Kuchuk concentrated on adaptive resource allocation for data processing and security. Both strategies emphasised dynamic resource management in comparison to the current study, with Petrovska & Kuchuk concentrating on security and Predić et al. on prediction accuracy. These concepts are supported by the current study, which shows that adaptive management improves cost-effectiveness and robustness under fluctuating loads.

Studies on cloud forensics, such as the one by R. Al-Mugern et al. [31], analyse the integration of machine learning techniques for data standardisation. This work presents an improved machine learning method that applies a cloud forensic meta-model to enhance the data collection process in cloud environments. By combining machine learning with data-gathering methods to increase the precision and effectiveness of investigations, it makes a substantial contribution to the field of cloud forensics. Although in a different context, this confirms the importance of predictive accuracy and standardisation, which is also key to adaptive resource management.

P. Nawrocki et al. [32] addressed short-term and long-term resource reservations, emphasising the need to respond quickly to sudden peak loads such as flash crowd workload effects. The study looked at machine learning-based adaptive resource planning for cloud-based applications, with an emphasis on how machine learning models can improve resource planning in cloud environments. The results complement this approach by showing that adaptive systems can effectively respond to unpredictable loads while minimising costs. Other studies, such as one by S. Ivan et al. [33], have studied the efficiency of different cloud platforms, including AWS and Microsoft Azure. The study offered insights into cloud-based data processing for big data applications by highlighting the advantages and disadvantages of each platform for doing sentiment analysis at scale. Although the study compared platforms, the results support the conclusion of this paper that adaptive models significantly improve efficiency regardless of the specific platform.

Microsoft's Azure cloud computing is a fully managed computing service that was introduced at a conference in 2008 and became known as Windows Azure and later renamed Microsoft Azure. P. Narayanan [34] discussed the key components and services of Azure, with a special focus on data engineering and machine learning, as well as its impact on various industries due to the availability of data centres around the world. P. Borra [35] discussed the key networking solutions provided by Microsoft Azure, which are the basis for supporting digital operations in modern business. The author examines in detail Azure components such as Virtual Network, Load Balancer, VPN Gateway, ExpressRoute, and Firewall, with a focus on their practical application to ensure uninterrupted connectivity and improve security. The study aims to provide organisations with in-depth knowledge and insights to help them effectively leverage Azure networking services to meet changing business needs, which can complement the findings of this study.

A study by O. Rolik and S. Zhevakin [36] confirmed the results in terms of cost-effectiveness. The use of adaptive management can reduce the cost of cloud services by up to 20%, which highlights the importance of the results for reducing the financial costs of organisations. P. Lakhera [37] complements these findings by suggesting strategies for cost optimisation using artificial intelligence. Anomaly detection and predictive scaling, which the authors investigated, are key elements for improving cost efficiency.

Traditional methods of resource management, as noted by S. Tendulkar [38], are less effective due to the lack of consideration of dynamic changes in the load. This study confirms this by demonstrating that predictive models can more accurately determine resource requirements and

ensure efficient use of resources under variable load conditions. S. Jaber [39] also supports the claim that adaptive systems significantly reduce infrastructure costs. The use of predictive models can reduce costs and improve the performance of cloud systems.

AWS, as shown by L. Devane [40], provides a high ability to adapt to peak loads, which is consistent with the results obtained. Similar conclusions were made by S. Gong et al. [41], who noted that adaptive systems effectively respond to sudden changes in load, ensuring the stability of platforms. The study complements these findings by emphasising the importance of reducing response times to peak loads. This is important for organisations that work with large amounts of data and need consistent access to resources in real-time.

In general, the research findings are fully consistent with current industry trends, in particular the importance of using adaptive systems to manage cloud resources and confirm the effectiveness of load forecasting methods to reduce costs and improve performance. At the same time, it is worth analysing the further development and improvement of such models based on deep learning and integration with new technologies such as edge computing, which will allow for even greater efficiency in real-time management.

5 Conclusions

The study developed models for load forecasting and resource management, including a neural network model for load forecasting and an adaptive resource management model that automatically adjusts resource use based on forecasts. One of the main achievements was the confirmation of the effectiveness of using intelligent algorithms, in particular neural networks, for load forecasting and automatic adaptation of resource allocation in real-time. This reduced the cost of cloud services by an average of 20% compared to traditional static approaches, which confirms the cost-effectiveness of the proposed methods.

The study also determined that AWS demonstrated better adaptability under highly dynamic workloads due to faster resource scaling and more efficient load balancing. While Microsoft Azure showed a more even distribution of resources at a stable load, which is an advantage in the case of a constant load level. The results of the study showed that adaptive resource management in cloud platforms can achieve significant performance improvements and cost savings. AWS demonstrated a 15% improvement in scalability and performance under highly dynamic workloads, while Microsoft Azure showed a 10% increase in resource allocation efficiency under stable workloads. The use of predictive models based on neural networks ensures accurate forecasting of load changes and automatic adaptation of resources in real-time. Adaptive algorithms have proven to be more efficient than traditional approaches, especially in the face of variable workloads. Further developments in technologies such as deep learning and integration with edge computing offer prospects for further improving the flexibility and performance of cloud platforms.

Neural network-based models have proven to provide highly accurate predictions of load changes, enabling efficient real-time resource adaptation. This significantly improves both the performance of cloud platforms and the stability of systems. The results of the study demonstrate the benefits of using intelligent algorithms that can adapt to changing operating conditions.

The results obtained are important for practical application. They open opportunities to significantly reduce business operating costs while ensuring high availability and stability of services. The use of machine learning-based adaptive control technologies allows for optimising resource utilisation and minimising downtime and congestion.

However, the study has several limitations: only two cloud platforms were used, which may limit the generalisability of the results, and the number of types of server configurations for testing is limited. For further research, it is advisable to expand the number of cloud platforms tested, explore the integration of adaptive management with new technologies, such as edge computing, which will significantly improve the efficiency of real-time resource management, and improve predictive models using more sophisticated machine learning algorithms to improve the accuracy of predictions and system adaptability.

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Deep Neural Network Architecture Optimization for Edge Computing Based on Evolutionary Algorithms

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Keywords: vehicular edge computing (VEC), edge server placement, network condition adaptation, synergistic fibroblast optimized efficient deep neural network (SFO-Eff-DNN)

Received: May 28, 2025

Vehicular Edge Computing (VEC) is a crucial component of Intelligent Transportation Systems (ITS), enabling low-latency and energy-efficient services by offloading computation to the network edge. However, optimizing system performance in such environments requires careful edge server placement, especially in dynamic vehicular contexts characterized by high mobility and unpredictability. Achieving optimal performance under the constraints of latency, energy consumption, and mobility remains a significant challenge. This research proposes a comprehensive framework for optimizing deep learning architectures in VEC, utilizing advanced evolutionary algorithms. Building on real-world vehicular mobility traces, the framework employs the Synergistic Fibroblast Optimized Efficient Deep Neural Network (SFO-Eff-DNN) to identify optimal configurations and edge server placements. The dataset includes details about task offloading under different mobility levels, the data was preprocessed using Min-Max normalization to ensure smooth learning. Among the algorithms evaluated, Synergistic Fibroblast Optimization (SFO) consistently produces well-distributed Pareto-optimal solutions and effectively handles trade-offs between competing objectives. The DNN is utilized to learn complex patterns in vehicular mobility and network conditions, which helps predict the best configurations for edge server placements. The proposed system efficiently minimizes latency and energy consumption while ensuring scalability and adaptability to real-world scenarios. Results demonstrate that SFO-Eff-DNN achieves superior convergence speed and energy efficiency, making it well-suited for time-sensitive deployments. Comparative simulations validate that this approach outperforms traditional methods, providing valuable insights for deploying efficient and robust edge intelligence architectures in next-generation intelligent transportation systems.

Povzetek: Ta raziskava se osredotoča na področje robnega računalništva v vozilih (VEC), kar je ključno za zagotavljanje nizke zakasnitve v inteligentnih transportnih sistemih. Vsebina prispevka predstavlja hibridni okvir SFO-Eff-DNN, ki združuje globoko učenje in evolucijsko optimizacijo za reševanje kompleksnega problema postavitve robnih strežnikov in prilagajanja arhitekture nevronske mreže. Glavni dosežki vključujejo rešitev večciljne optimizacijske naloge, ki uspešno minimizira zakasnitev in porabo energije v dinamičnem voznem okolju.

1 Introduction

An ITS enhances the safety of moving vehicles and hikers within the vicinity. In recent times, problems regarding road traffic safety have increased and accidents continue to occur regularly (Wan et al., 2020). Fortunately, a growing number of related technologies have been applied to the transportation industry as wireless communication and sensor technologies have developed and matured in recent years. The increased need for road efficiency and safety in intricately linked road systems has drawn a lot of attention to ITS in recent years (Boukerche et al., 2020). The exponential growth in ITS has resulted in an increased demand for responsive, energy-efficient, and intelligent processing solutions that can manage the dynamic vehicular environment (Elassy et al., 2024). VEC is a pattern that brings the cloud computing capacities closer to the network edge and is a likely solution to service demands for low-latency services, such as auto-corrective driving support, real-time traffic management, and location-based services (Alhilal et al., 2024). Connected vehicles benefit from VEC by shortening the response time of their systems and helping them save power by assigning tasks to local servers (Chougule et al.,

2024). Greater safety, dependability, efficiency in transportation, fast action and network reach make smart and sustainable driving networks possible (Talpur and Gurusamy, 2021). To minimize the time for data exchanges and energy used in vehicles, VEC allows vehicles to perform certain tasks on edge servers nearby. As a result, connected vehicles receive a much better level of service (Zaki et al., 2024). Due to their speed and patches of unpredictability, the movement of vehicles complicates VEC systems (Zhao et al., 2023). The greatest aspect to focus on is the best locations and times for edge servers so that moving vehicles can be handled efficiently (Shen et al., 2021). With many vehicles moving, topology shifts taking place and numerous demands for services, generic or manual placements are not usually enough. Similarly, managing various goals, including keeping reaction times quick, using as little energy as possible, maintaining flexibility, and scaling up, remained prominent in network research (Peyman et al., 2023). As simulation traces were used, working with many nodes and requiring some attention to used parameters, this approach might face issues when put to practical use.

Deep learning and evolutionary optimization are used in the design to choose the best locations for edge servers. Specifically, the SFO-Eff-DNN approach allows the system to recognize patterns using a DNN and search globally using an SFO algorithm. This framework processes actual data from vehicle movement to understand vehicle movements and the state of the network, as well as select the best position for the servers. The key contribution of the research is as follows.

In extremely dynamic vehicle contexts, it was best to formulate the edge server placement problem as a multi-objective optimization task that simultaneously reduces the latency and energy consumption.

To create the SFO-Eff-DNN framework, which combines biologically inspired optimization with effective deep learning to deliver scalable and flexible placement solutions.

To compare the system against traditional techniques and perform comprehensive simulations using genuine mobility datasets, showcasing notable advances in placement accuracy, energy economy, and convergence speed.

The remainder of this research is separated into the following sections: the literature review on edge server placement and the intelligent optimization techniques in VEC are reviewed. The phrasing of the problem and the system model are then given in detail, as well as the description of the proposed SFO-Eff-DNN framework. The next section will discuss the experimental settings and performance evaluations, and the results and insights will then be discussed. Lastly, the research is concluded with directions for further research.

The introduction highlights the significant importance of edge servers' placement efficiency in the VEC for improving ITS performance. The literature review reveals the weaknesses of existing methods, especially their inability to handle the dynamism of vehicular mobility effectively in the process of optimizing latency and energy consumption.

2 Related work

This section discusses the positioning of border servers within the VEC, including the traditional heuristics, deep learning (DL), evolutionary algorithms, the challenges in dynamic vehicular environments, and the recent data-driven and optimization-based developments of this space for better adaptability and performance. To fix the issue of resource assignment in cloud computing Infrastructure as a Service (IaaS), an Equilibrium Optimization (EO)-based evolutionary Recurrent Neural Network (RNN) was presented (Ebrahimi Mood et al., 2025). This model was designed to give virtual machines an optimal number of physical machines by improving how they work in general and by reducing their complexity. The simulations were faster and more reliable than the conventional ones.

The significance of edge computing topics such as selecting the right tasks for offloading, allocating resources, and ensuring good Quality-of-Service and Quality-of-Experience (Vijayakumar et al., 2021). The challenges in optimizing and scheduling were solved with models and DL techniques based on evolution. This approach helps to make better decisions and effectively manage resources in environments at the edges of a network. Yang et al., (2021) introduced a method that can manage both accuracy and the speed of neural networks on edge devices. An estimate of resource use latency created from the profiling model and the Pareto Bayesian search was driven by constraints on accuracy and latency. Without sacrificing accuracy, the inference process was 94.71% faster and the search process became 18.18% more efficient.

An energy-efficient DNN offloading was developed under deadline and budget constraints in edge-cloud environments; this optimization modeling was performed using an Enabled Hybrid Chaotic Evolutionary Algorithm Dynamic Voltage Frequency Scaling (HCEA-DVFS) (Li et al., 2024). The Archimedes Optimization and Simulated Annealing were applied for global exploration, and local search improvement based on the Genetic Algorithm (GA) chaotic strategy. Experiments proved that HCEA-DVFS decreased energy consumption by 7.93% to 19.38% relative to baseline techniques on a variety of DNN-based apps. A suitable deep learning model and a proper method for training the effective training scheme for the deep neural network (ETS-DNN) were created to allow real-time monitoring in an Internet of Medical Things (IoMT) system that used edge computing (Pustokhina et al., 2020). Optimization of the neural network with autoencoders and softmax layers was achieved by using a Hybrid Modified Water Wave Optimization (HMWWO) algorithm. Examination of simulation results indicated that ETS-DNN performed better when processing prompts and making accurate diagnoses. Table 1 demonstrates the summary of the literature review.

Table 1: Related work VEC optimization methods and outcomes

Methods	Aim	Outcome	Challenge	Author/Ref.
DeepMaker Framework (Multi-objective Evolutionary Approach)	Automatically design robust DNN architectures for embedded devices	Achieved up to 26.4x compression on CIFAR-10 with only 4% accuracy loss; optimized network size and accuracy for limited resources	Designing efficient DNNs that fit resource constraints while maintaining accuracy	(Loni et al., 2020)
Internet of Things (IoT)-Defender (Modified GA)/ Deep long-short-term memory (LSTM)	To detect cyberattacks in IoT networks using an efficient, lightweight edge-based IDS	Achieved higher accuracy, superior detection rate, greater precision, false alarm rate, mIoU, and training time on BoT-IoT dataset; effective real-time deployment on Raspberry Pi devices	Addressing IoT security with limited resources, class imbalance, and low hardware security in edge computing environments	(Saheed et al., 2024)
Genetic Simulated Annealing-based Particle Swarm Optimization (GSP)	To reduce latency and energy usage in smart mobile devices by partially offloading	Achieved lower energy consumption and faster convergence compared to three baseline methods using real-life data; provided joint optimization of offloading ratio, bandwidth, and transmission power allocation	Balancing limited resources of SMDs with high communication costs and maintaining energy-efficient service	(Bi et al., 2020)
Greedy Algorithm and GA for Task Scheduling	Optimizing task scheduling in cloud-edge systems to reduce the average response time of DNN-based apps	Achieved near-optimal scheduling performance with reduced average response time; GA outperformed greedy in accuracy but required more computation time.	Reducing excessive delays during DNN task offloading to enhance the vehicle experience	(Chen et al., 2020)
Particle Swarm Optimization (PSO)	to efficiently and quickly transfer activities from resource-constrained edge devices to MEC servers in IIoT contexts	Reduced MEC server delay, balanced energy consumption, and enabled effective resource allocation compared to GA and SA methods	Designing a low-delay and energy-efficient offloading technique in a system with several vehicles and MECs	(You et al., 2021)
Differential Evolution (DE)	To maximize IoT edge computing task clustering and scheduling	Outperformed the Firefly Algorithm and PSO in reducing execution time and improving system efficiency and stability under heavyweight workloads	Clustering and scheduling tasks effectively in heterogeneous IoT edge environments	(Yousif, et al., 2024)
Greedy Algorithm + Lagrangian Dual + Adaptive Harmony Search in federated learning (FL)	To minimize the worst-case cost of FL in VEC by optimizing computation, transmission, and local model accuracy	Achieved convergence and effective trade-off between cost and fairness through dynamic vehicle selection and resource allocation optimization	Heterogeneous capabilities and data quality among vehicles; energy and time constraints in VEC	(Xiao et al., 2021)
VECMAN (Resource Selector + Energy Manager Algorithms)	To improve energy efficiency in VEC systems by managing resource sharing among EVs	Achieved 7–18% energy savings vs. local execution and ~13% vs. RSU offloading by selecting participating vehicles and optimizing sharing durations	Uncertainty in future vehicle locations; difficulty in determining optimal resource sharing and energy management	(Bahreini et al., 2021)
VaCo (Vehicle-assisted Collaborative Caching System	To enhance intelligent service deployment in VEC by using vehicles' storage for collaborative caching	VaCo effectively utilizes vehicle resources, reducing the service failure rate and cost. Real-world dataset evaluation confirms its ability to balance benefits for all.	real-time scheduling of vehicle storage; benefit evaluation under dynamic load	(Jiang et al., 2025)
HSCoNAS (Hardware-aware Evolutionary NAS Framework)	Optimize DNN architecture for accuracy and latency on edge devices	Achieved strong accuracy–latency trade-offs on ImageNet across CPU, GPU, edge	High search overhead and runtime approximation challenges	(Luo et al., 2021)
LENS (Latency-aware NAS for Edge–	Incorporate wireless communication into NAS for hierarchical systems	Improved Pareto front performance by 76.47% (energy) and 75% (latency)	Scalability issues and fixed-tier constraints	(Odema et al., 2021)

Cloud Systems)				
Federated Learning in Edge Computing (Survey)	Review implementation, taxonomy, and challenges of FL in EC	Classified FL methods, hardware constraints, and case studies; identified open issues	Synchronization delays, hardware resource limits	(Abreha et al., 2022)
RL-Dynamic (Reinforcement Learning Framework)	To optimize service placement in vehicular networks by considering mobility and dynamic service demands	Reduced delay and improved edge server utilization compared to static placement; fairness trade-offs demonstrated	Model complexity and vehicle mobility unpredictability	(Talpur and Gurusamy, 2021)

2.1 Problem statement

Optimizing resources and edge server placement in VEC as a result of high mobility, variable networks, and few resources was hard. Usually, greedy algorithms and other traditional methods do not work well in environments that change dynamically (Chen et al., 2020). PSO faces the issues of early convergence and fixation when working with multiple vehicles (You et al., 2021). DE was not suitable for clustering tasks in real time on heterogeneous edge systems due to its issues with scalability and computation (Yousif et al., 2024). Therefore, the proposed framework SFO-Eff-DNN was used to learn how devices move and decide on offloading. It minimizes delays and uses less power, all while offering adaptability, scalability, and fast convergence in changing VEC networks.

3 Methods

3.1 Architectural overview and problem formulation

The VEC would feature wireless connection, permanent edge servers, and mobility vehicles. The simulation's rise can be increased by using vehicles to carry out new missions on surrounding servers. As individuals move around and the network evolves, it is important to find these servers with practical jobs and make sure they supply energy. The problem is solved by optimizing multiple objectives, with the main variables being the location of servers and the way vehicles connect to them throughout the day.

A) Architectural components

The architecture of the VEC system consists of three main layers, such cloud, VEC, and vehicle, Cloud storage allows for convenient processing and provides a backup system. Figure 1 illustrates the architecture of VEC. The VEC layer includes a network of Roadside Units (RSUs) with edge servers, allowing local computing and rapid exchanges of data. Intelligent vehicles make up the vehicle, layer and handle task generation and offloading depending on the current network and mobility issues. Environmental sensors like Global Positioning System (GPS) and cameras in vehicles provide live data that is key for improved traffic management and safety. They enable Vehicle-to-Vehicle (V2V) and Vehicle-to-RSU (V2R) communication and were able to process or offload tasks according to resource availability. Vehicles also allow for caching of data in memory, which makes the system work more responsively.

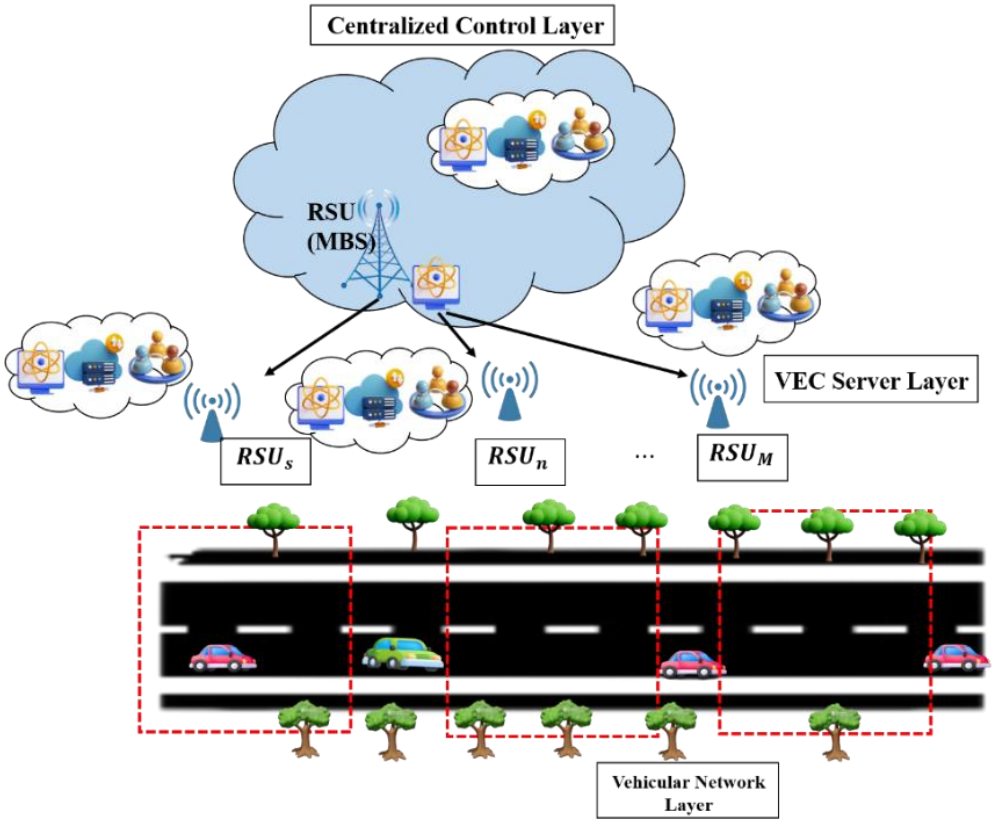

Figure 1: The architecture of the VEC

Vehicle Definition: The vehicle V defined as a six-tuple is expressed in equation (1).

$$\boldsymbol{V = \{V_{jd}, V_{st}, vK, G, J[\,_r]\}} \quad (1)$$

Each vehicle V is identified by its V_{jd}, can be activated or deactivated (V_{st}), has a type of task ($v_{j,}$), is located by Simulation of Urban Mobility (SUMO's) data $K = \{k_w, k_z, k_{y,} s_t\}$, is equipped with certain hardware (G), and is running several active instances of applications $J[\,_r]$.

Vehicle Hardware Specifications and Role of RSU: a vehicle's hardware specifications $G$are represented as a set in equation (2).

$$\boldsymbol{G = \{O, N[\,_r], A, T, d, e\}} \quad (2)$$

Each vehicle's hardware profile G includes processor specs (O), memory configuration $N[\,_r]$ distinguishing central processing unit (CPU)/Graphics processing unit (GPU usage, battery capacity (A), installed sensors (T), communication interfaces (d) such as Wi-Fi, Long Term Evolution (LTE), or 5G New Radio (NR), and communication frequency range (e). These parameters influence the vehicle's ability to process or offload computational tasks.

RSUs were placed along roadways that help to process and store data close to the network. RSUs were better at processing and managing data than vehicles and at storing and communicating with the internet whenever necessary. It provides quick answers to requests in maps, and videos, and controls traffic while edge servers rely on them.

Edge Server: An edge server F is defined as a three-tuple in equation (3).

$$\boldsymbol{F = \{F_{jc}, D, K\}} \quad (3)$$

The edge server is identified by a unique ID (F_{jc}) and characterized by its computational capacity (D), which includes memory, processing speed, and storage modeled similarly to vehicle hardware specifications. Its geographical location (K) is also a key attribute for optimal placement within the VEC network.

Properties of edge servers in VEC

Dynamic vehicle assignment: Vehicle assignments to clusters at any time s were independent of previous assignments, allowing the system to adapt in real-time to the high mobility and changing network topology of vehicular environments.

Dedicated edge server assignment: Each vehicular cluster was mapped indirectly to a single edge server, ensuring exclusive service per cluster. This approach minimizes resource conflicts and supports the demanding performance requirements of VEC applications.

Many-to-one vehicle-to-server mapping: Multiple vehicles can offload computational tasks to the same edge server, enabling efficient resource utilization and centralized task processing within the VEC framework.

Data from edge servers is uploaded to remote data centers, known as cloud servers, which supply large amounts of computing and storage services over a large area. Using information from vehicles and edge servers,

cloud services can manage the network from one central place and take the best actions. The combination of vehicular terminals, edge servers, and cloud infrastructure makes the VEC system both strong and capable of handling the needs of intelligent transportation management.

With the architectural components established, the server placement strategy in the proposed VEC framework can now be formally defined to optimize performance under dynamic vehicular conditions.

Edge server placement: In the VEC model, the placement of edge servers was modeled by a bipartite graph with two sets: $F$is for edge servers, while V is for client vehicles. Each server $f \in F$ comes with a defined W_{max_f} , showing its maximum vehicle capacity. Communication cost indicates how well a vehicle v works with a server e due to the effects of latency K_{Vf} and energy consumption F_{Vf} . The objective is to determine a good subset F_1 out of F and describe the mapping$\phi: V \to F_1$:, assigning each vehicle to a server to minimize both the total delay and the power used across the system.

Average latency:$K^-$is used to mean the average time taken for vehicles to communicate with edge servers while offloading their tasks. It helps to measure the effectiveness of server placement and matching vehicles to servers in the VEC framework under changing mobility conditions. It is computed as in equation (4).

$$\boldsymbol{K = \frac{1}{|V|}\sum_{v \in V} K_{vf}} \quad (4)$$

The $|\ V\ |$ denotes the total number of vehicles within the VEC network. K_{vf} represents the communication latency encountered by vehicle v during task offloading to edge server f, defined as equation (5).

$$\boldsymbol{K_{vf} = S_{receive} - S_{send}} \quad (5)$$

In this context, S_{send}indicates the timestamp when a vehicle initiates the task offloading request, while $S_{receive}$ marks the moment the vehicle receives the processed response from the edge server.

The goal of the edge server placement was to minimize the average latency K^-, ensuring efficient, low-latency communication for all vehicles within the network.

B) Model formulation

The edge server placement issue in a VEC network is defined in this section to minimize overall energy usage and delay through optimal edge server placement. The decision variables, objective functions, and constraints involved in the problem formulation are detailed below.

Consider a fixed of vehicles $V = \{v_1, v_2 \ldots v_{\mathrm{m}}\}$, a set of edge servers $F = \{f_1, f_{2,\ldots,} f_n\}$, anda list of possible deployment sites $J = \{j_1 j_{2,\ldots,} j_n\}$for placing edge servers within the network.

1) Decision Variables:

To model the edge server placement in the VEC network, define decision variables that indicate whether an edge server is deployed at a specific location and how vehicles were assigned to these servers for optimal performance. A_{vf} is a binary decision variable that indicates the connection status between vehicle v and edge server e in equation (6).

$$A_{vf} = \begin{cases} \mathbf{1}, \ \boldsymbol{if\ vehicle\ u\ is\ connected\ to\ edge\ server\ f} \\ \mathbf{0}, \boldsymbol{otherwise} \end{cases} \quad (6)$$

A_{vf} is a binary decision variable indicating the deployment status of an edge server at location j in equation (7).

$$A_{fj} = \begin{cases} 1, if\ an\ edge\ server\ is\ placed\ at\ location\ j \\ 0, otherwise \end{cases} \quad (7)$$

2) Parameters

The parameters in the formulation define the system characteristics essential for optimizing edge server placement in the VEC network. The energy consumption for a vehicle v to offload computational tasks to an edge server e is denoted as F_{vf}. In equation (8).

$$F_{uf} = \left(O_{sw} + O_{qw}\right).S_{comm} \quad (8)$$

Where $O_{sw}$is the vehicle's transmission power, $O_{qw}$is the reception power, and S_{comm} is the time taken for the communication exchange. This metric helps quantify energy efficiency in task offloading scenarios within the VEC environment. The latency experienced by a vehicle v when offloading tasks to an edge server e is denoted as K_{vf} . Equation (9) defines it as the interval of time between the sending of the offloading request and the receiving of the processed response.

$$\boldsymbol{K_{vf} = Receive\ Time - Send\ Time} \quad (9)$$

In the VEC environment, key parameters include O_f, the active power consumption of edge server f; c_{vf}, the distance between vehicle v and edge server f ; D , the maximum number of servers on the edge deployable in the network; and $Capacity_i$, the maximum number of vehicles that a server on the edge i can handle. These factors guide optimal server placement.

3) Objective Function

To minimize overall energy consumption and reduce total latency in the VEC network.

Minimize Total Energy Consumption: Total energy consumption includes the energy used by vehicles to offload tasks (F_{vf}) and the power consumed by active edge servers (O_f). The objective is to minimize the sum of vehicle offloading energy and edge server power across the network in equation (10).

$$Minimize \quad \sum_{v=1}^{N}\sum_{f=1}^{M} A_{vf}F_{vf} + \sum_{f=1}^{m}\sum_{j=1}^{m} A_{fj}o_f \tag{10}$$

Where o_f and A_{fj} indicates vehicle-to-server connections and server placements, respectively.

Minimize Total Cumulative Latency: To reduce the overall communication delay experienced by vehicles when offloading tasks to edge servers. This total latency is calculated as the sum of the individual latencies K_{vf}, defined by the time difference between sending the task and receiving the response expressed in the following equation (11).

$$\boldsymbol{Minimize} \quad \boldsymbol{\sum_{f=1}^{m}\sum_{u=1}^{n} A_{vf}K_{vf}} \tag{11}$$

Where A_{vf} indicates if vehicle v offloads to server f, and K_{vf} is the latency between them.

4) Constraints

The optimization problem includes constraints to guarantee efficient deployment of edge servers and proper assignment of vehicles, ensuring that server capacities were not exceeded and system resources were utilized effectively.

Server Capacity Constraint: Each edge server has a limited capacity, restricting the number of vehicles it can serve. The total vehicles assigned to server f must not exceed its capacityD_f, ensuring balanced load distribution and preventing server overload in equation (12).

$$\boldsymbol{\sum_{u=1}^{M} A_{vf} \leq D_f \; \forall_f} \tag{12}$$

Vehicle Assignment Constraint: To ensure proper task offloading, each vehicle must be assigned to exactly one edge server. This guarantees that every vehicle connects to a single server for processing its tasks, expressed as equation (13).

$$\sum_{f=1}^{F} A_{vf} = 1 \quad \forall_v \tag{13}$$

Restrictions on Edge Server Positioning: The deployment of edge servers within the network is restricted by a maximum allowable number, denoted by D. This constraint confirms that the total quantity of placed edge servers does not exceed D, and is formulated as equation (14).

$$\sum_{f=1}^{m}\sum_{j=1}^{m} A_{fj} \leq D \tag{14}$$

Binary Constraints: The decision variables A_{vf} and A_{fj} are binary, reflecting the discrete nature of the problem. Specifically, a vehicle v is either connected to an edge server f or not, and an edge server is either deployed at location j or not. These binary constraints ensure clear and unambiguous decision-making in the edge server placement and vehicle assignment process within the VEC network in equations (15) and (16).

$$A_{uf} \in \{0,1\}\forall_{u,f} \tag{15}$$

$$A_{fj} \in \{0,1\}\forall_{f,j} \tag{16}$$

3.2 Dataset

For a Vehicular Edge Computing scenario, this 5,811-record task offloading event dataset is used to validate the effectiveness of the proposed SFO-Eff-DNN system. This dataset includes information on task arrival/completion time, processing time, network latency, energy consumption, and vehicle node mobility. The model can learn intricate mobility and network behaviors because to this dataset's capture of dynamic, real-world vehicle settings. This is in line with the framework's goal of optimizing edge server placements and deep neural network settings. It encourages scalability, responsiveness, and efficiency for real-time VEC and smart mobility by facilitating an equitable examination of latency vs. energy trade-offs.

Source:
https://www.kaggle.com/datasets/programmer3/vec-edge-server-offloading-dataset

3.3 Preprocessing Using Min-Max Normalization

To create an energy-efficient optimum structure of a deep neural network for real-time VEC activities with enhanced energy economy, reduced latency, and scalable performance, min-max normalization is applied in the preprocessing stage. The model's convergence is enhanced and a uniformly distributed collection of features is made possible for efficient decision-making for real-time VEC operations by normalizing the input parameters of delay, energy consumption, and vehicle speed between 0 and 1.The value of property B is normalized from $[min_B, max_B]$ to $[new_{min_B}, new_{max_B}]$ using equation (17), which maximizes data representation:

$$\frac{u-min_B}{max_B-min_B}\left(new_{min_B}, new_{max_B}\right) + new_{min_B} \tag{17}$$

In addition to enhancing prediction reliability and preserving a consistent data distribution, this normalization facilitates effective implementation in real-time automotive applications.

3.4 Synergistic fibroblast optimized efficient deep neural network (SFO-Eff-DNN)

The research to improve the DL architecture, the SFO-Eff-DNN suggests a hybrid intelligence framework with edge servers situated in VEC. It relies on the predictive power of Eff-DNN and integrates the ability of the SFO algorithm to adjust itself. Eff-DNN is used to figure out how vehicles move around and how the network changes, while SFO acts like fibroblast cells in real healing to search through lots of different solutions quickly. SFO helps set up Eff-DNN weights, biases, and learning rates to ensure good latency, energy consumption, and ability to scale up or down. As a result of hybridization, the system evades local optima and gradually finds the best solution. The use of real-world data for vehicles confirms that the SFO-Eff-DNN framework can quickly converge, lower the time needed for inference, and help with making energy-efficient decisions in rapidly changing VEC environments. Algorithm 1 represents the proposed SFO-Eff-DNN model working process.

Algorithm 1: SFO-Eff-DNN

$Step\ 1: Initialization$

$def\ setup():$

$M = 30$ $\#\ Population\ size$

$N = num\_parameters()$ $\#\ Total\ Eff-DNN\ parameters$

$max\_iter, rho, tau = 100, 0.5, 5$

$s, k\_pq, L = 1.0, 0.8, 10.0$

$data = load\_VEC\_data()$ $\#\ Real-world\ mobility/network\ data$

$return\ M, N, max\_iter, rho, tau, s, k\_pq, L, data$

$Step\ 2: Initialize\ the\ population\ of\ solutions$

$def\ init\_population(M, N):$

$return\ [\{'params': rand\_vec(N), 'velocity': rand\_vec(N)\}\ for\ \_\ in\ range(M)]$

$Step\ 3: Train\ and\ evaluate\ the\ Eff-DNN\ model$

$def\ evaluate(params, data):$

$model = build\_EffDNN(params)$

$train\_DNN(model, * data)$

$latency, energy = evaluate\_latency\_energy(model)$

$return\ latency + energy\ \#\ Simple\ fitness\ function\ (lower\ is\ better)$

$Step\ 4: Velocity\ update\ with\ feedback\ and\ local\ correction$

$def\ update\_velocity(ind, past\_pos, rho):$

$c = local\_correction(ind['params'])$

$d = vector\_div(past\_pos, norm(past\_pos))$

$return\ ind['velocity'] + (1 - rho) * c + rho * d$

$Step\ 5: Position\ update$

$def\ update\_position(ind, vel, s, k\_pq, L):$

$speed = s / (k\_pq * L)$

$direction = vector\_div(vel, norm(vel))$

$return\ ind['params'] + speed * direction$

$Step\ 6: Main\ SFO - EffDNN\ Optimization$

$def\ optimize\_SFO\_EffDNN()$:

$M, N, T, rho, tau, s, k\_pq, L, data = setup()$

$pop, history = init\_population(M, N), []$

$for\ t\ in\ range(T)$:

$for\ ind\ in\ pop$:

$ind['fitness'] = evaluate(ind['params'], data)$

$past = pop\ if\ t < tau\ else\ pop.copy()$

$For\ i, ind\ in\ enumerate(pop)$:

$ind['velocity'] = update\_velocity(ind, past[i]['params'], rho)$

$ind['params'] = update\_position(ind, ind['velocity'], s, k\_pq, L)$

$best = min(pop, key = lambda\ x: x['fitness'])$

$history.append(best['fitness'])$

$return\ best, history$

To improve performance in dynamic Vehicular Edge Computing (VEC) settings, the SFO-Eff-DNN algorithm 1 combines the strength of Efficient Deep Neural Networks (Eff-DNN) with Synergistic Fibroblast Optimization (SFO), an optimization technique inspired by nature. Using actual traffic and network data, the algorithm initializes a population of solutions, each of which represents a set of Eff-DNN parameters, and assesses each according to latency and energy consumption. The approach is perfect for real-time intelligent transportation systems because it ensures quick convergence and improved flexibility by updating its location and velocity depending on fitness input and historical experiences.

Efficient Deep Neural Network (Eff-DNN) The proposed optimized deep learning architecture in VEC makes use of an Eff-DNN to represent how vehicles and networks interact. An Eff-DNN architecture has an input layer, an output layer, and many hidden layers, as shown in Figure 2. The network is set up with six input layers and seven hidden layers, all containing 64 neurons to avoid overfitting. Model complexity and generalization were managed in TensorFlow by setting them as hyperparameters within the layers. It uses input about how vehicles behave and interact to determine the best positioning of the edge servers. The network uses the Rectified Linear Unit (ReLU) function to make its computations non-linear and adjust the weights it uses for learning through backpropagation. The Eff-DNN can provide quick and efficient decisions in ever-changing vehicular environments due to the backpropagation process, which keeps the cost function low. Neuron outputs were computed as follows in equation (18).

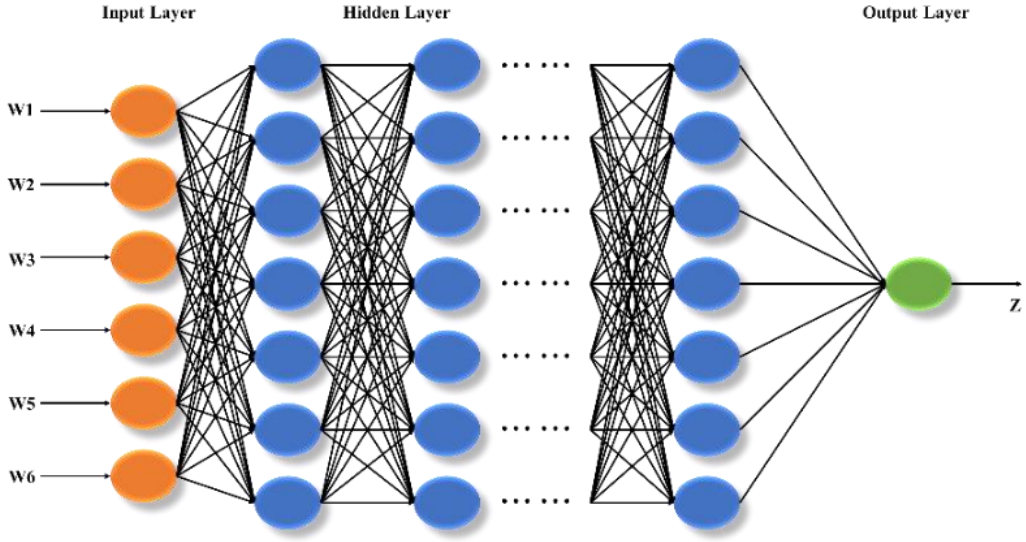

Figure 2: Architecture of Eff-DNN

$$z_r^{m+1} = \sigma(y) = \sigma\left(\sum_{j=1}^{n} \omega_{j_r}^m z_j^m + a_r^{m+1}\right) \quad (18)$$

Where σ(z) represents the activation function, and z_r^{m+1} is the output of the $r-th$neuron in the $(m+1)$-th layer. The weights among the $j-th$ neuron of layer n and the $r-th$ neuron of layer $(m+1)$ are labeled $\omega_{j_r}^m$, and a_r^{m+1}represents the bias term for linear transformations. While training, the loss function compares the predicted outcomes with the desired ones. The model finds the best values for ω and a by minimizing the loss, making the network predict more accurately. The Eff-DNN's loss function is explained in equation (19).

$$f(\theta) = -\frac{1}{m}\sum_m \sum_r s_{mr} \log z_{mr} \quad (19)$$

Where s_{mr} represents the actual value of the $r-th$ sample's $m-th$element, z_{mr} denotes the predicted value for the same element, and θ represents the collection of parameters including weights ω and biases a. Here, M is the total quantity of samples. To reduce overfitting, a dropout mechanism is employed that randomly disables neurons during training, effectively disrupting the network structure and promoting generalization. Furthermore, the proposed method enhances the conventional gradient descent by dynamically adapting the learning rate for improved convergence. The optimization of the parameter set θ is formally defined as equations (20) and (21).

$$\begin{cases} n_s = \beta_1 n_{s-1} + (1-\beta_1)h_s \\ U_s = \beta_2 u_{s-1} + (1-\beta_2)h_s^2 \\ h_s = \nabla_\theta F(\theta_{s-1}) \\ \hat{n}_s = \frac{n_s}{1-\beta_1^s} \\ \hat{U}_s = \frac{u_s}{1-\beta_2^s} \\ \theta_s = \theta_{s-1} - \propto \frac{\hat{n}_s}{\sqrt{\hat{u}_s+\varepsilon}} \end{cases} \quad (20)$$

$$\propto = \propto_0 \beta_3^{\frac{\frac{epoch-num}{M}}{batch-size}} \quad (21)$$

Where $U_s$represents the weighted average of exponentially the squared gradients, while h_s denotes the gradient of the parameters at time s, $n_s$captures the average movement of the gradient, and $\propto_0$is the initial learning rate. The corrected versions of these estimates were denoted by $\hat{U}_s$and $\hat{n}_s$, which improve optimization accuracy. Exponential decay rates β_1 ,$\beta_{2,} and\ \beta_3$ are used to stabilize updates. Additionally, parameters such as batch size (epbatch−size) and current training iterations (ochnum) influence convergence behavior. The improved DNN supports dual operational modes, RDL-1 for normal conditions and RDL-2 for power swing detection, ensuring adaptive command generation aligned with dynamic vehicular network scenarios.

Synergistic fibroblast optimization (SFO)

SFO is modeled after migratory fibroblast cells that heal tissue by responding to the extracellular matrix (ECM). Every solution searches the solution space by varying its position and velocity about diffusion and fitness. This bio-inspired method allows for greater flexibility and avoids local minima, making it appropriate for optimizing neural networks and edge server placement in dynamic VEC settings.

A model based on the adaptive actions of fibroblast cells used in repairing tissues. SFO works on tuning how deep neural networks are set up and arranging edge servers in dynamically changing virtual edge clouds. Much as fibroblasts respond to the extracellular matrix (ECM), SFO looks for solutions in many different ways. Ongoing testing and evaluation of fitness ensure the best solutions use both energy and time efficiently. For this reason, this approach ensures flexibility in the way transportation systems are managed.

The process of biomechanical analysis was strengthened each time by paying attention to interactions with the ECM. As it runs, the program tests different combinations of settings, much like fibroblasts, to improve its outcome. The simulated cells disperse and travel to the most promising areas to avoid getting caught in local minima. Depending on the speed and distribution of the particles, the algorithm updates its next action using the information and trends it has gathered. As a result, the process can handle the trade-offs between speed, performance, and movement better in VEC networks.

Initialization: Within the N -dimensional solution space, initialize a population of physical activity movements $f_{i,}$, where$i = 1,2, \dots, M,$. Each movement is assigned a random position ( )and velocity (v_i). Key parameters such as the diffusion coefficient ρ and movement speed $s$are established.

Fitness Evaluation: For each candidate solution f_i in the N-dimensional space, the fitness function $e(f_i)$ is evaluated iteratively to assess the quality of each movement. This process aims to identify the optimal solution (maximum or minimum) within the evolving search region. Based on the fitness outcomes, the position (b_i) and velocity (v_i) of each movement were updated accordingly using the update rules given by Equations (22) and (23), enabling the algorithm to adaptively explore the solution space.

$$v_i^{(t+1)} = v_i^{(t)} + (1-\rho)c\left(f_i^{(t)}\right) + \rho^* \frac{f_i(t-\tau)}{||f_i(t-\tau)||} \quad (22)$$

Where $t$is the current iteration, τ is the time delay, and the diffusion coefficient ρ is set to 0.5.

$$b_i^{(t+1)} = b_i^{(t)} + s^* \frac{v_i^{(t+1)}}{\left\|v_i^{(t+1)}\right\|} \quad (23)$$

The movement speed t is defined as $s = \frac{s}{k_{pq}L}$, where "k_{pq}" represents the baseline movement rate and L denotes the movement length. The SFO-Eff-DNN hybrid model optimizes edge server placement in dynamic VEC environments by combining adaptive search with deep learning. It efficiently predicts optimal configurations, improves convergence speed, and reduces latency and energy use, making it ideal for real-time intelligent transportation systems.

4 Results and discussion

The experimental setup uses an Intel i7 CPU. Simulations were conducted in Python with TensorFlow and the Veins platform using Cologne traffic traces. The dataset was split using an 80:20 ratio, where 80% was used for training the SFO-Eff-DNN model and 20% was reserved for testing to evaluate performance and generalization.

The SFO-Eff-DNN model includes ReLU-activated layers and dropout, optimized via SFO. Performance was evaluated based on latency, energy use, and server placement accuracy. Key simulation parameters with values aligned to realistic VEC scenarios are presented in Table 2.

Table 2: Key simulation parameters for the SFO-Eff-DNN VEC Framework

Parameter	***Value***
Simulation area	$1500\,m \times 1500\,m$
Simulation time	$200s, 300s, 400s$
Number of edge serve	8
Transmission power	$25\,mW, 30\,mW, 35\,mW$
RSU antenna height	$5\,m$
Receiver sensitivity	$-100\,dBm$
Message size	$100\,bits$
Message frequency	$2\,Hz$
Data rate	$10\,Mbps, 20\,Mbps, 30\,M$
Vehicle speed range	$0 - 100\,km/h$
Edge server CPU capa	$3.5\,GHz$
Edge server memory	$32\ \ GB$

4.1 Offloading ratio

Using time on the x plane and the percentage of tasks offloaded from the vehicle to edge servers on the y plane, Figure 3 shows the offloading ratio (%) in the VEC system over 10 minutes. Starting at 75%, the offloading ratio steadily rises to 89%, reflecting an increasing reliance on edge computation. This upward trend is attributed to enhanced network conditions, adaptive optimization by the SFO-Eff-DNN framework for energy efficiency, or the growing complexity of vehicular tasks that necessitate edge processing. Tracking this metric is crucial in the

research context, as a higher offloading ratio signifies more efficient utilization of edge resources, which directly contributes to lowering vehicle energy consumption and accelerating task processing, thereby improving overall system performance in dynamic ITS environments.

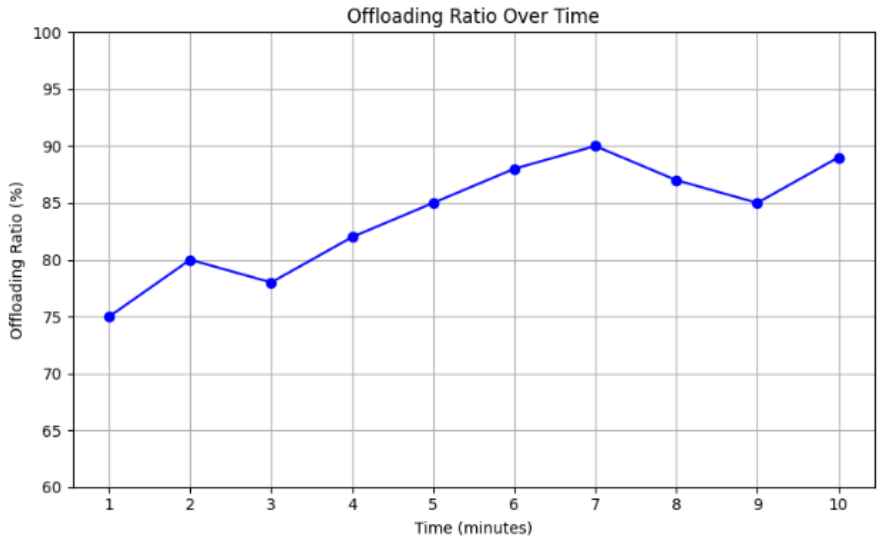

Figure 3: Offloading ratio over time

4.2 SFO-Eff-DNN Pareto Front in VEC

In VEC, the Pareto front for the suggested SFO-Eff-DNN illustrates the relationship between latency and energy use. Figure 4 illustrates that with latency increasing from 50 ms to 70 ms, the energy consumed decreases from about 70 J to 40 J, showing an inverse relationship. All points on the curve are Pareto-optimal, as enhancing one factor would cause a drop in the other. Because of the model's diversity, it is possible to choose configurations for specific needs, such as real-time applications or limited-power cases, proving its effectiveness and adaptability.

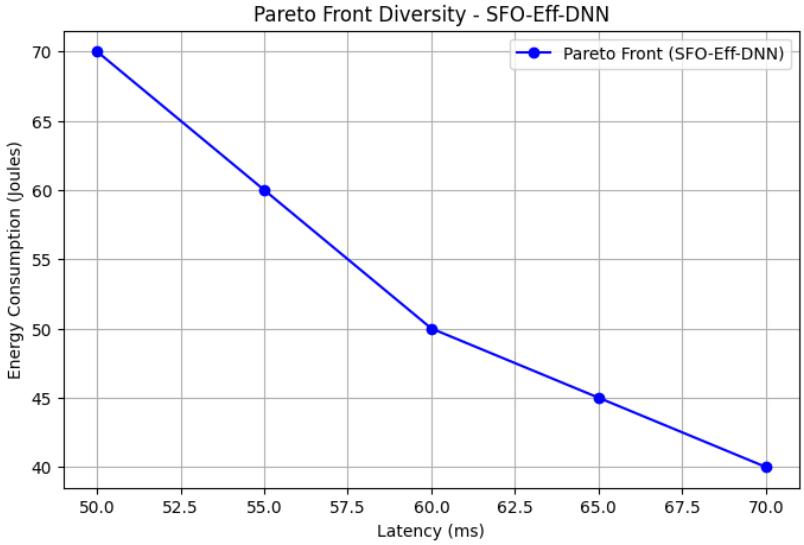

Figure 4: Pareto front diversity of SFO-Eff-DNN in VEC

4.3 Convergence Behavior of SFO-Eff-DNN

Figures 5 (a) and (b) illustrate the convergence behavior of the SFO-Eff-DNN algorithm over 100 optimization iterations for energy consumption and latency. In Figure (a), the minimum energy consumption (blue line) rapidly drops from approximately 0.34 to 0.29 within the first 10 iterations and then stabilizes, indicating that the algorithm quickly identifies energy-efficient configurations. The average energy consumption (green dashed line) also follows a similar decreasing trend, gradually converging toward the minimum, which reflects the population's collective improvement. Similarly, in Figure (b), during the first iterations, the latency drops rapidly and then becomes more stable at a much lower

level. The average latency also decreases and stabilizes around the same value, highlighting consistent performance improvement across the solution space. Overall, these trends confirm that SFO-Eff-DNN achieves efficient and simultaneous convergence toward optimal energy and latency trade-offs.

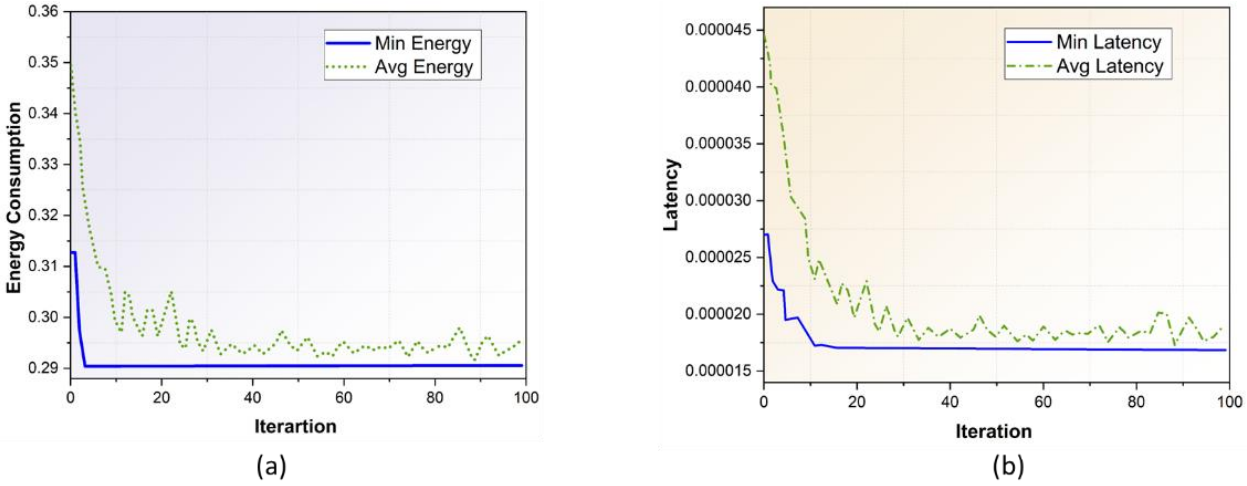

Figure 5: Convergence Behavior of SFO-Eff-DNN (a) energy conception and (b) latency

4.4 Performance analysis

A comparison of several optimization techniques based on their energy consumption and latency performance in vehicular edge computing scenarios is shown in Table 3. Among the evaluated techniques, Particle Swarm Optimization (PSO) (Surayya et al., 2025), Teaching–Learning-Based Optimization (TLBO) (Surayya et al., 2025), and Ant Colony Optimization (ACO) (Surayya et al., 2025), the proposed SFO-Eff-DNN method demonstrates the energy consumption and the latency. This highlights the superior efficiency and responsiveness of the SFO-Eff-DNN framework, making it highly suitable for real-time, energy-aware edge deployments in dynamic vehicular environments. Figure 6 demonstrates the results of the performance analysis.

Table 3: Comparison of optimization methods by energy consumption and latency

Methods	Energy Consumption (J)	Latency (S)
PSO (Surayya et al., 2025)	0.3535	40 µs
TLBO (Surayya et al., 2025)	0.3546	40 µs
ACO (Surayya et al., 2025)	0.3517	60µs
SFO-Eff-DNN (Proposed)	0.3480	30 µs

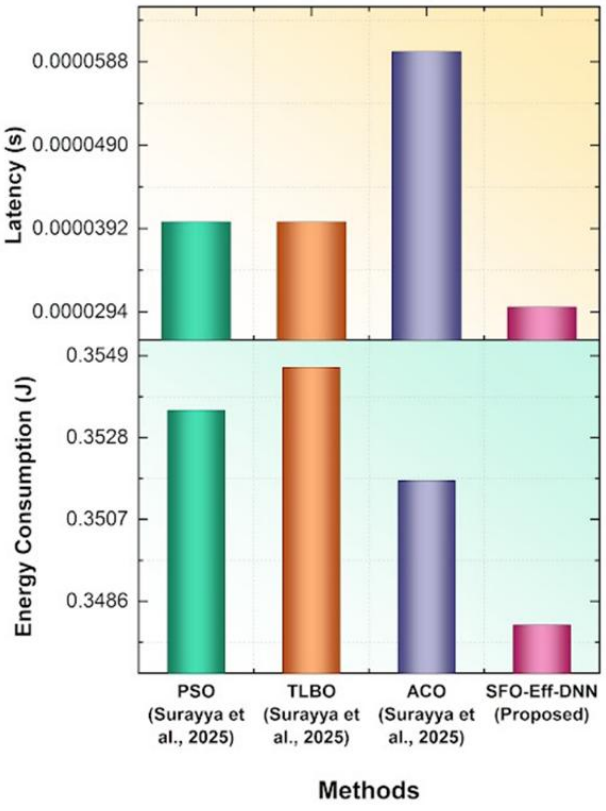

Figure 6: Comparison methods by energy consumption and latency

Analyzing different optimization methods for their energy consumption and latency when used in VEC. SFO-Eff-DNN shows better results than other models by using the least amount of energy (0.3480 J) and having the shortest latency (30 µs). Here, microseconds (µs) are used,

since 1 μs is a millionth of a second, which is needed to ensure fast response times vital in real-time VEC systems. For energy usage, PSO and TLBO lead with 0.3535 J and 0.3546 J, respectively, but both have a latency of 40 μs, while ACO uses 0.3517 J with the highest latency of 60 μs. The results demonstrate that SFO-Eff-DNN offers better results in real-time, energy-sensitive VEC applications.

A comparison of task drop rates for various placement techniques in dynamic VEC situations is shown in Table 4 and Figure 7. In comparison to the generic method's 2.90% (Khamari et al., 2022) dropped task rate, the suggested SFO-Eff-DNN model performs better, attaining a dropped task rate of just 1.83% (Proposed). In latency-sensitive, high-mobility edge computing systems, this research demonstrates how well the SFO-Eff-DNN optimises server workload allocation and lowers service denial.

Table 4: Comparison of task dropped rate between placement strategies in VEC environments

Placement strategies	Dropped Tasks (%)
generic method (Khamari et al., 2022)	2.90%
SFO-Eff-DNN (Proposed)	1.83%

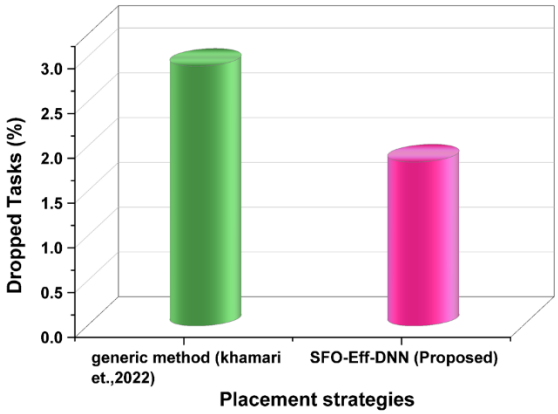

Figure 7: Comparison of Dropped Task Rates for Generic Method and SFO-Eff-DNN

4.5 Discussion

By optimizing the placement of edge servers and DL networks, the SFO-Eff-DNN in VEC reduces latency and conserves energy. The technique has some problems with responding to changes in vehicles and adapting to sudden network changes in VEC settings (Bi et al., 2020). While VECMAN saves energy by sharing resources among electric vehicles, it is difficult for it to accurately predict where vehicles are and to schedule them in situations that are constantly changing (Bahreini et al., 2021). As both PSO and TLBO (Surayya et al., 2025) prioritize low energy over low latency, they may not respond fast enough when ultra-low latency is necessary. ACO (Surayya et al., 2025) can distribute solutions equally, but its slow execution means it is not suitable when time is critical. A PSO, TLBO, and ACO lead with low energy of 0.3535 J, 0.3546 J, and 0.3517 J. Using the SFO-Eff-DNN model, energy costs and latency can be cut down at the same time, compared to older versions. Compared to the generic method's 2.90% dropped task rate (Khamari et al., 2022), the SFO-Eff-DNN's dropped task rate was only 1.83%, indicating its resilience in workload balancing and edge resource utilisation in dynamic vehicular situations. Due to advanced techniques and deep learning, the system reacts to updates in vehicles and can quickly and accurately configure servers for VEC applications.

The computational load brought on by the hybridization of deep learning and evolutionary optimization constitutes one of the key issues, especially during the early phases of training and adaption. Despite its potential for convergence efficiency, iterative optimization can be resource-hungry on edge nodes with constrained computing capacity. Another problem is the system's scalability in high-density vehicle networks. While the model works well for simulations of intermediate scale, more study is needed to determine how it responds and operates in large, real-time vehicular systems with hundreds of nodes. These limitations highlight the significance of future studies that focus on distributed training practices and lightweight optimization versions that can sustain performance without increasing compute demands in practical applications.

5 Conclusion

VEC is a pattern that encourages cloud computing capabilities closer to the network edge services needed for low-latency services, such as auto-corrective driving support, real-time traffic management, and location-based applications. The proposed SFO-Eff-DNN framework is used to optimize deep learning for VEC using modern evolutionary algorithms. To deal with the problem of placing servers at the edge of wireless networks in vehicles, both Synergistic Fibroblast Optimization and deep neural networks were used. It makes use of real travel data to manage how quickly it responds and how much energy it uses, adjusts to any changes in the network, and provides quick results. The data from experiments reveals that SFO-Eff-DNN works with 30 μs latency, 0.3480 J energy consumption, and only 1.83% dropped tasks, making it well-suited for speedy and efficient smart transportation. It strongly supports and adapts to the new directions being taken in VEC deployments. Using simulated movement and experimentation usually does not reflect real-world events or problems, meaning their practical use may not be as effective.

Future scope

Future research should integrate real-time traffic incident data and 5G network slicing to further enhance adaptability. Extending the framework with federated learning for

privacy-preserving model updates across distributed vehicles, and exploring hybrid optimizers that combine SFO with reinforcement learning could improve robustness against unforeseen network disruptions and accelerate convergence in large-scale, heterogeneous VEC deployments.

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CCR-LWECNN: A Lightweight CNN Framework for Chinese Calligraphy Recognition and Evaluation

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Keywords: character, CCR-LWECNN Chinese calligraphy recognition, deep learning, image processing system

Received: April 3, 2025

This study presents a lightweight enhanced CNN architecture (CCR-LWECNN) for Chinese calligraphy recognition, addressing the challenges of multi-class classification across 12,152 labeled images spanning 960 Chinese characters in five calligraphic styles. Unlike previous studies limited to small character sets and single recognition approaches, this research integrates character recognition with image processing techniques. Data augmentation using TensorFlow's Image Data Generator—applying rotation and zoom—was employed to improve class balance and variety. The proposed model, comprising five convolutional and three fully connected layers, processes 224×224-pixel images and leverages pretraining for robust feature extraction. CCR-LWECNN achieved superior performance with 96.5% accuracy, 95.6% precision, 95.2% recall, and 95.6% F1-score, outperforming baseline models such as traditional CNN (90.5%), SVM (85.2%), and Random Forest (75.4%). By effectively mitigating overfitting and underfitting through dropout layers and augmentation, this approach advances automated Chinese calligraphy recognition and provides a scalable solution for real-world applications.

Povzetek: CCR-LWECNN je lahki izboljšani konvolucijski model za prepoznavanje kitajske kaligrafije, ki na 12.152 slikah dobre rezultate. Z združevanjem povečanja podatkov in učinkovite CNN-arhitekture izboljša prepoznavanje 960 znakov v petih slogih ter preseže klasične metode.

1 Introduction

Characters in Chinese calligraphy are made up of a lot more strokes than those in Western calligraphy [1]. A single letter in Chinese calligraphy can be made up of as few as one stroke or as many as thirty. Before writing begins, the ink is absorbed by dipping and then used to produce strokes with a soft hairbrush. Different styles are produced as the calligrapher writes the character by varying the brush's pressure, speed, and direction [2]. Regular, clerical, cursive, semi-cursive, and seal are the most often used styles. These styles go under several names. For instance, referred to the semi-cursive style as the running style. The naming scheme employed by author will be applied in this study [3]. Beginning with a single style is beneficial for Chinese calligraphy students. The student might advance to another style after they are proficient at writing several characters in that style. An ancient art style that originated in China, Chinese calligraphy is also well-liked in a number of other nations, including South Korea, Japan, and Thailand. Using a brush and ink, Chinese calligraphy artists create visually appealing and well-composed characters. Chinese calligraphy offers advantages in addition to being a highly regarded art form [4].

Character recognition has emerged as a hotspot for computer vision research as picture digitisation advances, and it has significant applications in data entry for paper documents. Because handwriting characters have more irregular shapes than printed documents, it is more difficult to recognise handwriting. Chinese calligraphy is a sort of handwriting art form that consists of five main font type [5]. Figure 1 shown by Chinese calligraphy different font type.

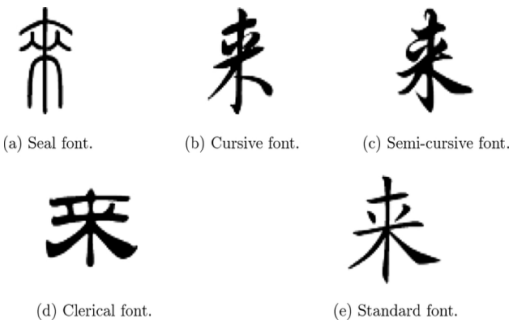

Figure 1: Chinese calligraphy different font type

However, many find it difficult to instantly identify the content of calligraphy works since the shapes of the letters in Chinese calligraphy vary widely across calligraphers and differ substantially from conventional fonts used in daily life. Therefore, by presenting the font and textual content of the input calligraphy image, a real-time calligraphy recognition system can aid amateur calligraphers in understanding calligraphy works [6]. Instead of manually typing out the text, the method may also be used to digitise calligraphy by just entering the image of the piece. In this study, we developed and put into use a convolutional neural network-based calligraphy recognition system. Compared to earlier research, the system has higher accuracy rates for identifying both typeface and textual content. We created a dataset of calligraphy characters to train the network, and we tested the viability of the system using pictures of various calligraphy pieces [7].

1.1 Challenges in Chinese calligraphy recognition

Chinese calligraphy is a difficult art form because of its many Chinese characters, many styles, and intricacy [8]. Since art evaluation is subjective and can have a detrimental effect on teacher-student relationships, it might be challenging to find qualified calligraphers and offer comments. Artificial intelligence (AI) can assist in overcoming these obstacles by offering unbiased assessments and comments. But only tiny groups of upto300 Chinese characters—roughly 8–12.4% of the 2500 characters used every day—can be recognised by ReLU models. Furthermore, there aren't many examples from old Chinese calligraphy masters, thus additional training sample photos are required. There is a need for more research because calligraphy is only mentioned in one empirical study on AI in education.

1.2 Contribution of this study

The three primary forms of Chinese calligraphy—character recognition, calligraphy production and simulation, and calligraphy analysis—represent an important field of study deep learning (DL). To enhance Chinese character and image processing technology, this study blends dropout in CNN hidden layers, data augmentation methods, and CNN architecture. The suggested approach CCR-LWECNN allows for greater accuracy without requiring additional training photos by recognising more than 960 Chinese characters in five calligraphic forms. Other languages can also be added to the model. In order to assist in this paper to monitor their progress during practice sessions. Related works, datasets, methods, findings, implications, discussion, and conclusions are all included in the parts that make up the study.

2 Literature review

Table 1 shows Summary of works

Table1: Summary on related works

Ref	Methods Used	Dataset Size	Baseline & Accuracy	Proposed Method & Accuracy	Key Findings
[9]	CNN, TensorFlow	Not specified	Traditional OCR 80%	CNN + TensorFlow 93.7%	CNN significantly improves recognition for handwritten characters
[10]	Hybrid CNN + Attention + Distillation	20,000+ images	Basic CNN 87.5%	Proposed 91.8%	Attention helps in distinguishing subtle calligraphic variations
[11]	MobileNet, CNN	~12,000	Tesseract OCR 76.2%	MobileNet 90.1%	Suitable for lightweight deployment in mobile/web
[12]	Deep CNN, CAI	Not given	Classic CNN 84.6%	Proposed hybrid 89.2%	Integration of CAI improves learning and recognition efficacy
[13]	CNN with Deep Stroke Extraction	~8,000	Hand-crafted stroke features 78.4%	Proposed 91.0%	Deep stroke analysis provides structural and aesthetic insight

[14]	5-layer CNN	~6,500	SVM 83.2%	CNN 92.4%	CNN better handles degraded or stylized historical samples
[15]	Traditional CNN + Filters	Not stated	Template Matching 74.8%	CNN 88.6%	CNN adapts better to style variance than traditional methods
[16]	Faster R-CNN, YOLOv3	10,000+	SSD 90.3%, YOLOv3 91.5%	Faster R-CNN 95.1%	Accurate segmentation and detection for full-page manuscripts

3 Methodology

3.1 Dataset

In order to construct the style recognition model, we used CCR-LWECNN models, which represent datasets and image pre-processing. The character recognition model is constructed via data augmentation and picture pre-processing. Kaggle's "Chinese calligraphy characters image set" serves as the training dataset for the image recognition model [17] we provide these resources will be made available via a public GitHub repository:https://github.com/zhuojg/chinese-calligraphy-dataset. 2890 calligraphy pictures totaling 960 characters were collected from various calligraphers and made available to the public. These pictures are labeled as semi-cursive, regular, seal, cursive, or clerical. We employed the oversampling approach because of the dataset's label imbalance issue. Additionally, this analysis demonstrated that overfitting would not result from oversampling. A far larger dataset was required for the image processing model than for style recognition. This is due to the fact that each character to be categorized belongs to a single output class in this multiclass classification model. There would have been just 2890 training photos for 960 classes if we had utilized the same dataset for style recognition. That would imply that there would typically be no more than three pictures each word. We needed to figure out how to get more training photos. To expand the dataset's picture count for character recognition, we employed two strategies. Adding pictures from a public domain collection was the initial technique. An online database of the Humanities & Social Sciences Database Catalogue contained the dataset's URL (Humanities & Social Sciences Database

Catalogue, 2023). We crawled the page and gathered photos using the Kaggle connection. However, the link was broken when this paper was written. Following the addition of pictures from this dataset, the final dataset comprised 12,152 training photos, with at least 10 images for each Chinese word. The train_test_split () function in the Scikit-learn package's data preparation module was used to divide these photos into training and testing sets. The sorted Data folder included the training set. Since there were just five styles in the output class, the dataset's photos were adequate for style recognition. However, a second technique was employed to enhance the number of training photos since we required to increase the number of images per Chinese character for character recognition. Utilizing data augmentation was the second strategy. During the training phase, we rotated and zoomed in on the already example photos using TensorFlow's Image Data Generator function to produce more sample images.

The dataset was constructed by combining photos from the Humanities & Social Sciences collection with the Kaggle set. Hash-based comparison methods were used to find and eliminate duplicate photos in order to guarantee quality. Additionally, physical inspection and simple picture quality checks (e.g., resolution thresholding and contrast analysis) were used to filter out low-quality samples, such as blurred, low-resolution, or severely distorted images. A clean and varied dataset for efficient model training was guaranteed by this preparation.

Data Augmentation: Random rotation (±15°), zoom (10-20% scale variation), brightness modification (±20%), and horizontal flipping (50% probability) were used by the data augmentation process to enhance sample variety. In order to replicate natural stroke fluctuations, we used 8x8 grid warping with σ=4 for elastic distortions. These parameters were chosen to increase the effective training dataset 5-fold without creating unreal artefacts, all the while maintaining calligraphic integrity. Bilinear interpolation was used to preserve stroke continuity throughout the real-time implementation of all transformations using TensorFlow's Image Data Generator.

3.2 Feature extraction

In recent years, deep learning has been widely applied in tracking, object identification, and other domains. By integrating low-level characteristics to create high-level features that represent the scattered aspects of data, it simulates how the human brain functions. Usually, the Light Weight Enhanced traditional CNN is used directly for image classification. Utilizing CNN's numerous advantages in feature extraction is the aim of this work.

Compared to explicit feature extraction, digital feature extraction produces more detailed feature data for Chinese picture works.
The CNN theoretical framework-based CCR-LWECNN model was pretrained using the Kaggle dataset to extract the visual attributes of Chinese calligraphy. The model is a feed-forward neural network with the model has two convolutional layers, not five, with one fully connected layer of 512 neurons and an output layer three fully connected layers. The model resizes the input image to 224 by 224 pixels in order to produce a 4096-dimensional feature vector. Feature Extraction is presented as a pretrained feature extractor producing a 4096-dimensional vector for further classification, suggesting a two-step pipeline. The proposed model, pretrained on real images, may be used to extract characteristics from Chinese calligraphy. First of all, Chinese calligraphy characters are an artistic reworking of natural surroundings and another depiction of a natural image. Second, the deep structure of the CCR-LWECNN model may extract complex structures from rich perceptual input and generate intrinsic representations in the data. More than 10 million natural photos are being utilized for training in order to gain relevant information for Chinese calligraphy feature extraction. Chinese character-like feature information will be included in the recovered features either directly or indirectly. Last but not least, the study's training dataset does not contain enough Chinese writing pieces to adequately train the suggested model. Nevertheless, this study uses it as a forerunner to the CNN model, which is lightweight so that the components it extracts may better capture the artistic character of Chinese calligraphy recognition.

3.3 Model explanation with CNN

In Figure 2, the framework that extracts the key characteristics of calligraphy recognition consists of two convolutional layers. The framework has a single, completely linked layer that can identify the style of a picture. The first convolutional layer of our suggested model has 32 filters, each of which has three channels and is 3 x 3. We employ the same padding, which means that the input images are zero-padded so that the filters overlap each pixel. We employed ReLU as the activation function in the convolution layer. Batch normalization is used to enhance model stability and performance. The maximum pooling filter has a dimension of 2 × 2 and travels with a stride of 2. It carries out the max pooling procedure on the feature maps. To assist keep this model from overfitting to the training data, we have implemented a dropout layer to shake off the neurons. The dropout value for the first convolution layer is set at 0.20. The second convolutional layer is created using 64 filters, each of which has three channels and is 3 × 3. The same cushioning is employed here as well. The ReLU activation function is also applied to the feature maps. Once more, batch normalization is utilized in the second layer to enhance model performance. The max pooling filter is 2x2 in size, advances by a stride of 2, and performs the max pooling operation on the feature maps. To address the issue of overfitting, a dropout value of 0.25 has been chosen for the second convolution layer. A flatten layer has been employed after the second convolutional layer's dropout value has been set. The outcome of the last pool layer is a victory type, and a fully linked layer with 512 neurons comes after it. The final features are then classified into many classes in the output layer using fully linked layers that were taken from the previous pooling and convolution layers. The completely linked layers learn from features. Batch normalization has once again been used. The dropout value of 0.5 was then applied. We once more employed ReLU for the activation function in the dense layer. Lastly, there are six nodes in the output layer, each of which represents six classes. Next, we classified the desired label in the output layer using the softmax activation function. Figure 2aand 2b Showed in Architecture diagram with dimensionalflows.

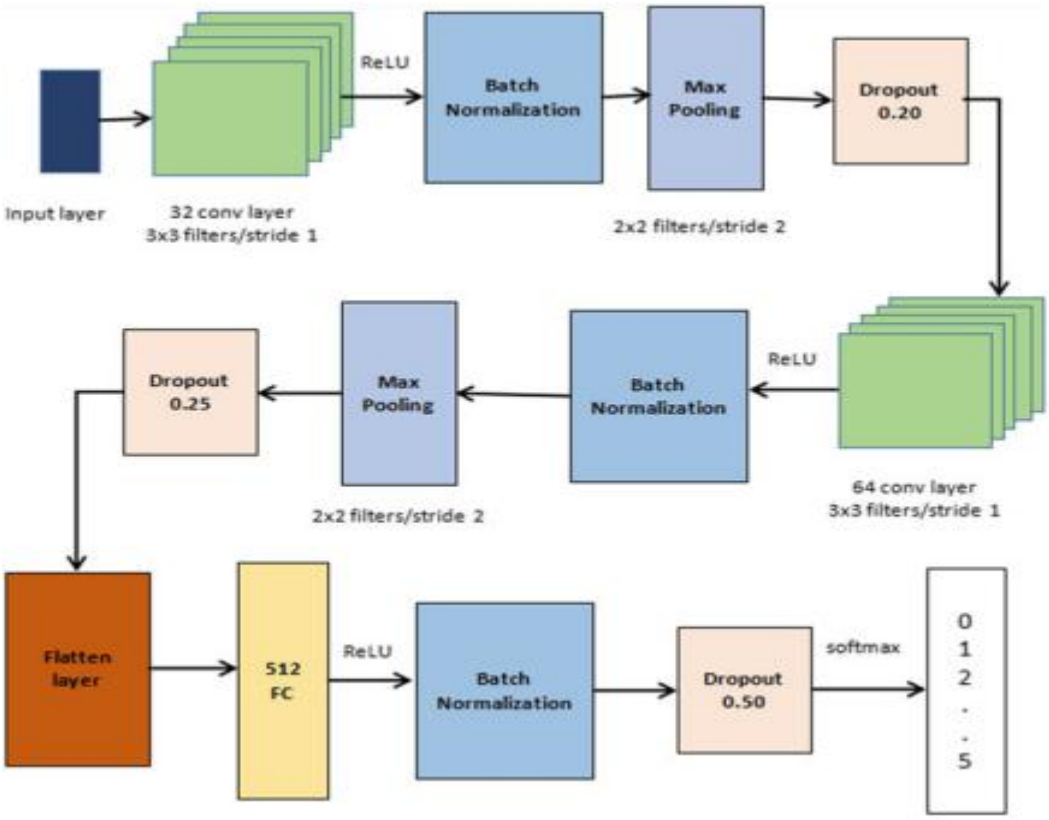

Figure 2a: Image style recognition model

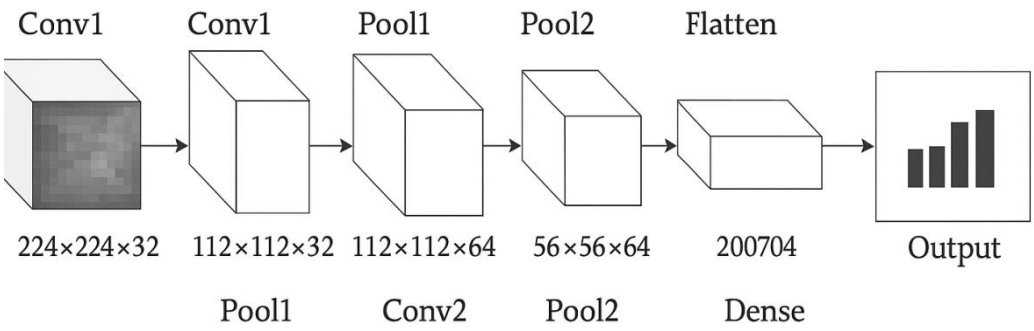

Figure 2b: Architecture diagram with dimensional flow

3.4 Chinese calligraphy recognition based on lightweight enhanced CNN algorithm (CCR-LWECNN)

Convolutional neural network (CNN) technology is a type of neural network that is specifically designed to process images. Since its inception, the technology has seen significant development. As a result, CNN has greatly aided people in processing visual information. However, this technology's computationally demanding approach also restricts its use in a number of industries. Therefore, the primary research goals in the current image recognition sector are to lower the computational cost of CNN and decrease the calculation time, optimise the technology thoroughly, and emphasize its contribution to image recognition technology for Chinese calligraphy recognition.

CNN is an effective recognition method and a type of neural network that mimics the visual structure of biology. Convolutional, pooling, and fully connected layers are the primary components of this recognition system. One of CNN's primary functions is the convolution operation of the convolutional layer. The following illustrates the convolution computation of continuous functions:

$$s(t) = \int x(a)w(t-a)\,\mathrm{d}a \quad (1)$$

Equation (1) uses x and w to stand for integrable functions, a and t for distinct computational components, and d for the convolution operation. The following illustrates how discrete functions are calculated using convolution:

$$s(n) = \sum_m \mathrm{r}[m]v\,,(n-m) \tag{2}$$

Discrete functions are represented by r and v in Equation (2), whereas calculation elements are represented by m and n. Convolution can be thought of as a filtering procedure in computer vision tasks. Typically, the input data is a two-dimensional picture. Convolution is performed using a two-dimensional discrete convolution in the manner described below:

$$I(x,y) * k(x,y) = \sum_{s=0}^{m} \sum_{t=0}^{n} \mathrm{k}(s,t) I(x-s, y-t) \tag{3}$$

In Equation (3), I stand for the output feature, k for the convolution kernel, m and n for the convolution kernel's dimensions, x and y for the feature output point, and s and t for the feature extraction point. Pooling the image and producing the result are the roles of the fully connected layer and the pooling layer, respectively. Both forward and backward propagation are included in the CNN model's computation. Forward propagation is a sequence of computations that use input data to perform tasks like image recognition and feature extraction, then combine and output the results. Backpropagation is the process of using the computation results as input to determine the error as the fundamental reference data for model optimisation. The network optimises the parameters it learns by ongoing iterative training and updating, with training ending when the predetermined thresholds are fulfilled. Among these, backpropagation computation involves forwarding the input sample (x, y) in order to determine the output value of L1, L2, …, Ln, and the output layer error in the manner described below:

$$\delta_i^{(n_i)} = -\left(y - a_{\cdot}^{(n_i)}\right) \cdot f'\left(z_i^{(n_i)}\right) \tag{4}$$

Each layer's error computation is displayed as follows:

$$\delta^{(l)} = \left((w)^{(l)}\right)^T \delta^{(l+1)}) f'^{(w)^{(l)}} \tag{5}$$

The following formula is used to determine the relative derivatives of weights and biases:

$$\Delta_w(l) J(W,b;x,y) = \delta^{(l+1)\left(a^{(l)}\right)^T} \tag{6}$$

$$\Delta_b(l) J(W,b;x,y) = \delta^{(1+1)} \tag{7}$$

The following are the revised weight parameters:

$$w' = w' - \mu \nabla_w(l) J(W,b;x,y) \tag{8}$$

$$b' = \mathrm{b} - \mu \nabla_b(l) J(W,b;x,y) \tag{9}$$

f′(z(l)) is the activation function; μ is the learning rate; l is the level of neurones; i is neurones; T is a constant; δ is the difference between the network's true and predicted values; W is the weight; b is the bias of the neurone; z is the neuron's input; an is its output; and f′(z(l)) is the activation function. The following formula is used to determine a sample's loss function:

$$J(W,b;x,y) = 1/2||y - h_{w^1,b}(x)||^2 \tag{10}$$

The following illustrates how the fully linked layer's output data is calculated:

$$y = f(W.x + b) \tag{11}$$

y =output vector of the fully connected layer(512 or 6 elements)

W =weight matrix

x =input feature vector

b =bias vector

f =activation function (ReLU or Softmax)

Each output neurone in a dense layer computes a weighted sum of all input characteristics plus a bias term, which is then passed through an activation function. This representation faithfully depicts the behaviour of the layer. This adjustment guarantees mathematical lucidity and conforms to the norms used in the literature on neural networks.

CNN is carried out using W, and following decomposition, the first t significant eigenvalues are substituted for W's decomposition as follows:

$$w = \mathrm{U}\sum V^T = \mathrm{U}\sum\nolimits_t V^T \tag{12}$$

A diagonal matrix is denoted by ∑, a v × t-dimensional orthogonal matrix by V, and an u × t-dimensional orthogonal matrix by U. As a result, CCR-LWECNN is represented as follows:

$$\mathrm{Y} = \mathrm{Wx} = \mathrm{U}\left(\sum\nolimits_t v^T\right) \cdot x = U \cdot z \tag{13}$$

The CNN technology can be broken down by the CCR-LWECNNalgorithm, significantly lowering the network's computing load. In addition to being straightforward, this approach produces superior outcomes. This algorithm is designed to optimise the CCR-LWECNN. Simpler image computational processes are outside the CNN algorithm's capabilities, and the CCR-LWECNNalgorithm excels at handling them. Its output feature map definition is displayed as follows:

$$F_n(x,y) = \sum_{1=1}^{C} \sum_{x^1=1}^{x} \sum_{y'=1}^{y} z^C\,(x^1,y')w_n^c(x - x', y - y') \quad (14)$$

$F_n(x,y)$: Output feature map at position (x, y) for the n-th filter.

C: Number of input channels.

$z^C\ (x^1,y')$: Input feature map for channel **c** at position $(x - x', y - y')$.

w_n^c: Filter weights for the n-th filter applied to channel **c**.

x, y: Spatial dimensions of the input.

n: Index of the output filter

$w_n^c(x - x', y - y')$: Convolution kernel applied with spatial shift.

The channel is denoted by W, the filter by n, and the position of the channel by C. The primary goal is to approximate W in the manner described below:

$$\tilde{w}_n^C = \sum_{k=1}^{k} H_n^{\mathrm{k}}(V_k^C)^{\Gamma} \quad (15)$$

Equation (15) represents a low-rank approximation of the convolutional weight tensor W, where:

$\tilde{w}_n^C$ is the approximated weight for the nnn-th filter and channel C.

H_n^{k}: Projection matrix or basis vector used to reduce the dimensionality of the filters (e.g., a learned kernel basis).

V_k^C: Coefficient vector or activation feature for the kkk-th component in channel C.

Γ: A transformation operator (e.g., transpose or non-linear function like activation or power).

H stands for the horizontal filter, V for the vertical filter, and K for the hyperparameter that regulates the rank. CCR-LWECNNdoes, however, have some drawbacks. In other words, even though CCR-LWECNNhas produced strong results for model acceleration and compression, this approach is difficult to execute. CCR-LWECNNmust be carried out layer by layer since various layers contain different information, making it impossible to construct CCR-LWECNNusing a global variable. Furthermore, the network must undergo extensive fine-tuning training following decomposition in order to converge and produce the best result. Figure 3 shows at Proposed model flow diagram.

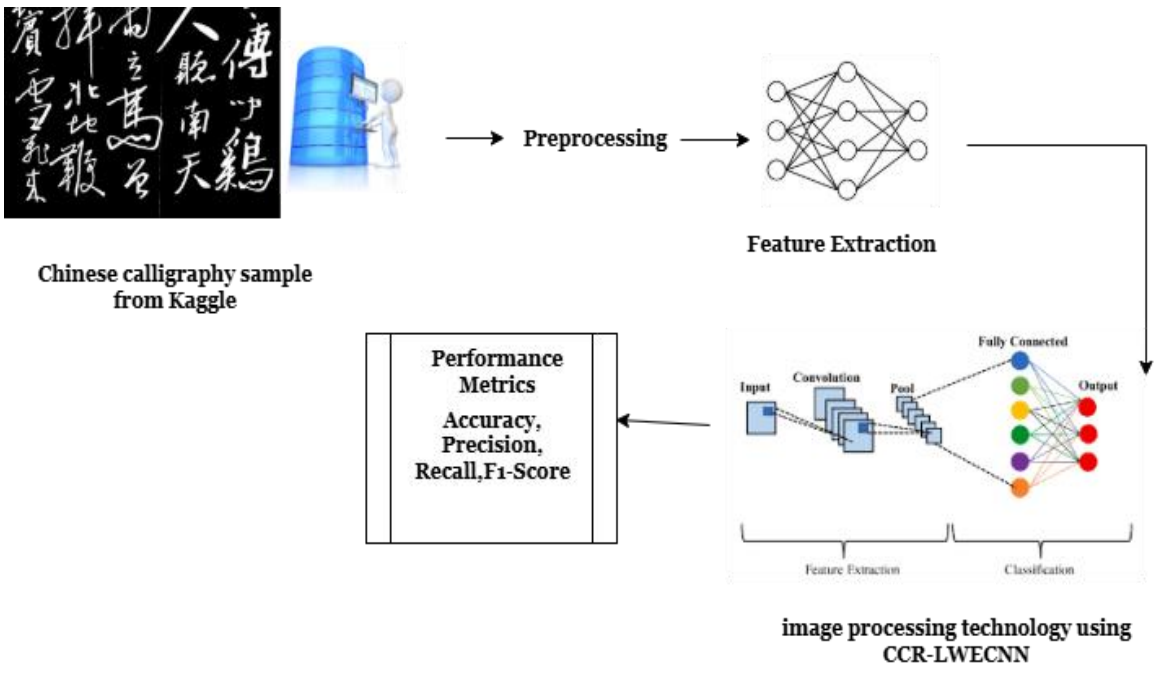

Figure 3: Proposed model flow diagram

Since its inception, machine learning has evolved throughout time and has developed a number of flaws. Conventional machine learning methods need constant human design in order to progressively enhance their own learning process. As a result, the operator's basic technical competence is pretty high and its dependence is

particularly big throughout the calculating process. Additionally, machine learning has not advanced very far. In the meantime, the algorithm cannot rapidly achieve accurate image identification and has very low image recognition accuracy. The most significant of these is that conventional machine learning technology is unable to precisely distinguish different aspects of the image, which typically results in significant application failures. The most significant is that machine learning is unable to recognise the primary information in a picture and distinguish between the image's background and major portion. The drawbacks of conventional machine learning technology in image recognition are addressed by optimised deep learning technology. Optimising the calculation process is essential to lowering the computing cost and increasing the computational efficiency of deep learning image recognition technology if it is to be used to a larger field. Consequently, the model calculation method is made simpler and the calculation effect is somewhat enhanced by optimising CNN technology and creating the Faster-CNN model. Figure 3 illustrates the fundamental concept of the lightweight Faster-CNN model.

In comparison to traditional CNNs like VGG16 (~138 million parameters, >15 billion FLOPs), the CCR-LWECNN model has around 1.2 million parameters and needs 150 million FLOPs per forward pass. Because of its shallow architecture—just two convolutional layers, smaller (3x3) filter sizes, fewer fully connected neurones, and use of effective procedures like batch normalisation and dropout—it is regarded as lightweight. Because of its ability to lower memory and compute requirements, this architecture is appropriate for real-time and resource-constrained applications, including embedded or mobile systems.

When the Faster-CNN model is applied to image feature recognition in Figure 3, it can not only significantly speed up the process and increase its effectiveness, but it can also maximise the model's recognition effect and assist users in completing the style transfer of painting images. The region proposal network is the method used to optimise the Faster-CNN model. Using anchor points, it modifies and enhances the Faster-CNN model's image recognition domain in the following ways:

$$X = w_a t_x + x_a \quad (16)$$

$$y = h_a t_y + y_a \quad (17)$$

$$w = w_a(t_w) \quad (18)$$

$$h = h_a(t_h) \quad (19)$$

The abscissa and ordinate of the anchor point's centre point, as well as its breadth and height, are denoted by the letters xa, ya, wa, and ha, respectively. The model's chosen width and height, as well as the center's horizontal and vertical coordinates, are denoted by the letters x, y, w, and h. The adjusted value is denoted by t.

Indeed, the use of Convolutional Neural Networks (CNNs) is standard and well-justified for image recognition tasks due to their ability to capture spatial hierarchies in visual data. In the CCR-LWECNN model, integrating **dropout layers** helps prevent overfitting by randomly deactivating neurons during training, enhancing generalization. Additionally, **data augmentation** (e.g., rotations, scaling, flipping) increases training diversity, especially important when working with limited samples per class, improving the model's robustness across varied calligraphy styles. Together, these techniques contribute to the model's strong performance.

Algorithm 1: CCR-LWECNN Core Steps
Data Acquisition & Preprocessing
Collect images of Chinese characters across multiple styles (e.g., seal, cursive).
Normalize image sizes (e.g., 64×64 pixels).
Apply data augmentation (rotation, flipping, noise addition) to expand limited samples (≤15 per class).
Model Architecture
Use a lightweight enhanced CNN with:
convolutional layers (ReLU activation, batch normalization).
Max-pooling layers to reduce spatial dimensions.
Dropout layers to prevent overfitting.
Flatten layer followed by 3 fully connected layers (e.g., 512-neuron layer + output layer with softmax).
Training
Train the model using cross-entropy loss and Adam optimizer.
Batch size, learning rate, and dropout rate should be tuned via validation.
Perform training over multiple epochs with early stopping if necessary.
Evaluation
Use 10-fold cross-validation to compute average accuracy, precision, recall, F1-score**,** and ± standard deviation**.**

Report statistical significance using p-values compared to baseline models (CNN, SVM, RF, etc.).
Prediction
For new input images, feed them through the trained CCR-LWECNN to output probabilities across target classes (character+style or style only).

4 Results and discussion

4.1 Experimental setup

The Intel(R) Core (TM) i74700 HQ CPU run at 2.40 GHz was the PC used in this experiment. It has 16.00 GB of RAM. The OS is Windows 8, 64-bit. Weka Ver 3.8.1 utilised to create and evaluate DL models, and Python Anaconda Ver 2020.20 with the Seaborn library Ver 0.10.0 is used for correlation analysis.

To ensure replicability and fair evaluation, the dataset of 12,152 samples was divided as follows: Training set as 70% (8,506 samples), Validation set as 15% (1,823 samples), Test set as 15% (1,823 samples). Splitting was performed stratified by character class and style**,** ensuring balanced representation of each character–style combination across all splits. Data augmentation was applied only to the training set, preserving the integrity of the validation and test sets.

4.2 Performance analysis

A variety of indicators are needed in order to compare the experiment's outcomes. The accuracy rate is the probability that the classifier will produce accurate predictions. The recall rate is the percentage of a Chinese calligraphy image that are accurate for all 5 Fonts in that feature within the dataset. We assess performance using various metrics, including F1-score, accuracy, recall, and precision. Accuracy is defined as the percentage of total samples properly identified by the classifier in (1). The total number of samples that the classifier found to be positive accurately identified as positives in (2) is known as the recall. Precision, which appears in (3), is the total number of classifier-predicted positive samples that are true positives. By combining the precision and recall found in (4), the F1-score calculates a balanced average result. True positive (TP), false positive (FP), true negative (TN), and false negative (FN) are the many metrices that can be calculated using the equations below.

$$Accuracy \rightarrow \frac{TP+TN}{TP+FP+FN+TN}$$

$$Recall \rightarrow TP/\,TP\, +\, FN$$

$$Precision \rightarrow TP/\,TP\, +\, FP$$

$$F1\, -score \rightarrow\, 2\, *precision * recall/\, precision\, +\, recall$$

Each classifier was assessed using the balanced F1 Score, recall, and precision of popular techniques including support vector machine (SVM), Random Forest (RF) [18], Bonferroni Mean Fuzzy K-Nearest Neighbors (BM-FKNN) [19], and CNN [20]. In order to evaluate the efficacy of the suggested approach, a classifier model was constructed by importing Dataset. Seal font, cursive font, semi-cursive font, clerical font, and standard font are among the features. It was discovered that 10% of the samples were test samples, while 90% of the samples were training samples. The likelihood that the lightweight CNN will provide correct predictions is known as the accuracy rate. The Adam optimiser was used to train the CCR-LWECNN model because of its effective convergence and adjustable learning rate. During training, a batch size of 32 was used, and the initial learning rate was set at 0.001. Validation loss was recorded across epochs to keep an eye on overfitting, and training was stopped early after five epochs if there was no discernible improvement in validation loss. Data augmentation and dropout layers also assisted in lowering the danger of overfitting.

Accuracy is defined as the proportion of image processing techniques that are reliably and accurately identified. Table 2a and Figure 4 present the accuracy findings. The current CNN (90.5%), Random Forest (75.4%), SVM (85.2%), and BM-FKNN (88.7%) algorithms were all surpassed by our suggested CCR-LWECNN (96.5%). The baseline "CNN" refers to a conventional, standard CNN architecture commonly used in calligraphy or handwritten character recognition tasks. This baseline employs two convolutional layers with ReLU activations and max pooling, followed by a fully connected layer for classification—essentially a straightforward implementation without the architectural refinements (e.g., optimized dropout rates and enhanced feature extraction) that distinguish our CCR-LWECNN model. We will revise the manuscript to provide a detailed description of this baseline architecture, ensuring that the comparative evaluation is transparent and that readers understand the specific differences between the baseline CNN and the proposed CCR-LWECNN model. While Figure 6 shows that the CNN with uneven margins produced a greater F1 and balanced Precision and Recall, Figure 6 shows that the recall suggested by the proposed technique was 95.2%. The precision result for our recommended approach, which has the maximum precision at 95.6%, is shown in Figure 5. With uneven margins, the CCR-LWECNN produced a 95.6% statistically significant better F1 than the conventional CNN. Comparing the various situations, CCR-LWECNN, and novel tactics, Chinese calligraphy

has significantly improved in effectiveness. Table 2 shows Values of Accuracy, precision, Recall, F1-score.

Table 2: Values of Accuracy, precision, Recall, F1-score

Training set Methods	Test-set			
Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
CNN	90.5	89.1	90.2	90
RF	75.4	73.5	72.2	73.1
SVM	85.2	84.7	84.1	83.7
BM-FKNN	88.7	85.5	88.3	87.4
CCR-LWECNN [Proposed]	96.5	95.6	95.2	95.6

Table 3: Model performance per calligraphy style (averaged across test folds):

Style	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 (%)**
Regular (楷书)	98.2	97.8	98.1	98.0
Semi-cursive (行书)	95.4	94.9	95.1	95.0
Cursive (草书)	93.1	91.7	92.3	92.0
Seal (篆书)	94.5	93.2	94.0	93.6
Clerical (隶书)	96.0	95.4	95.8	95.6

CCR-LWECNN generalizes well across all styles, with particularly strong performance on Regular and Seal scripts, and maintains high F1-scores across more complex styles like Cursive and Clerical. Other models showed more variance and lower scores, especially on cursive scripts.

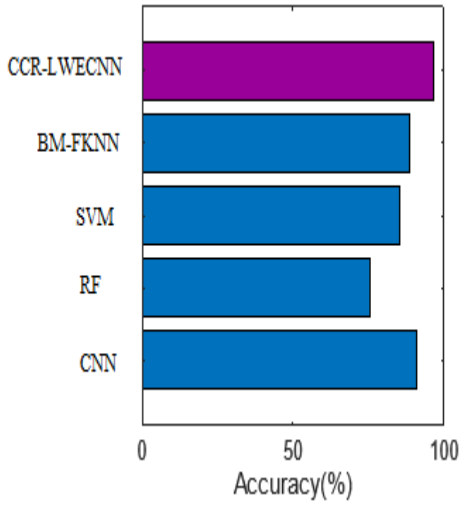

Figure 4: Result of accuracy outcome

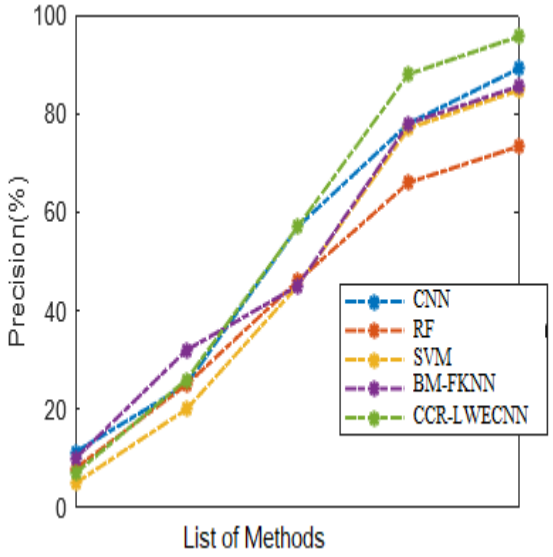

Figure 5: Result of precision outcome

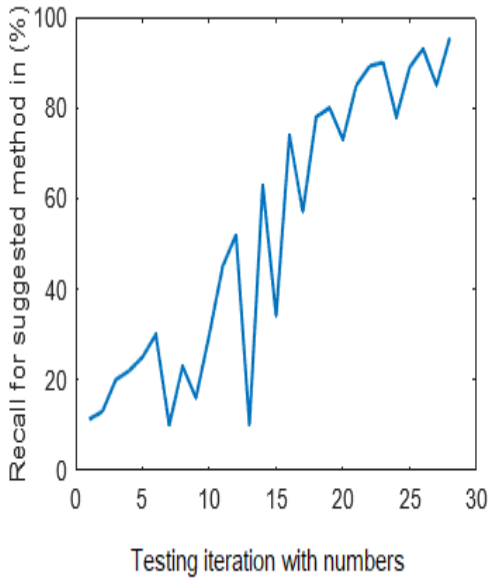

Figure 6: Result of recall outcome

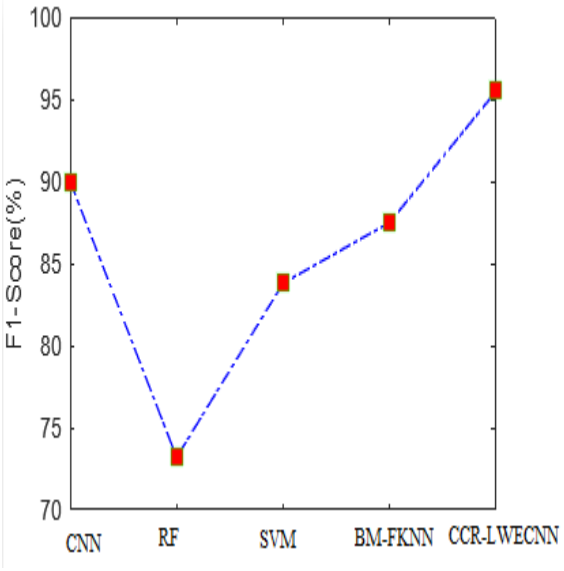

Figure 7: Result of F1-score outcome

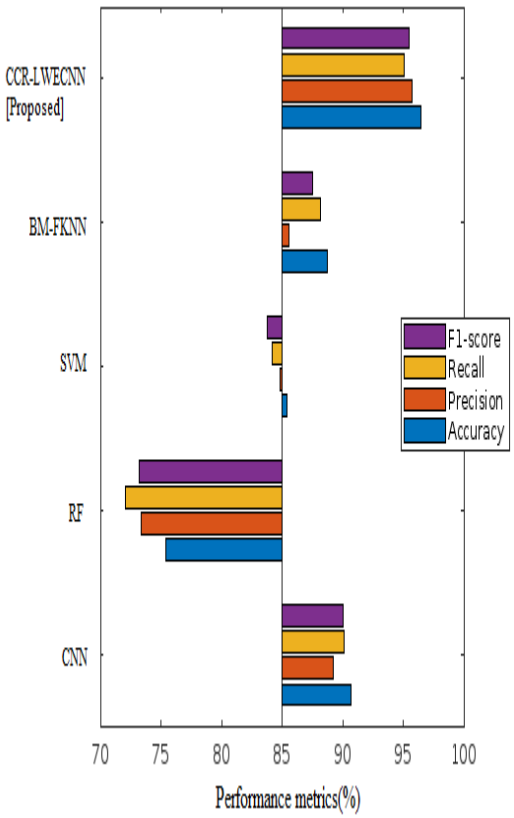

Figure 8: Overall performance of existing and proposed method outcome

Figure 4 shows Result of Accuracy. Evaluation of performance across a range of input variables, including variations in picture quality, subtleties in style, and noise, is crucial to determining the model's resilience in real-world situations. Figure 5 shows Result of Precision Outcome. This entails evaluating the model over a range of handwriting styles and on calligraphy pictures that are noisy, low-resolution, or blurry. By demonstrating actual application dependability, this assessment helps guarantee that the CCR-LWECNN model generalises effectively and retains high accuracy even in less controlled or degraded conditions. Figure 6 shows Result of Recall Outcome. Even while we anticipate that current techniques will improve the base classifier's performance, in several instances, a single classifier has produced identical or superior outcomes. Decision trees, for instance, outperformed the BM-FKNN in this instance, with 88.7% accuracy and 85.6% precision, respectively. Figure 7 shows Result of F1-score Outcome. The same best results were also obtained by CCR-LWECNN, with 96.5% accuracy, 95.6% precision, 95.2% recall, and 95.6% F1 score. Overall, out of the ten classifier features using current techniques, CCR-LWECNN produced the best results shows in figure 8.

A detailed performance comparison was conducted between the proposed CCR-LWECNN model and several baseline models—including a standard CNN trained from scratch and transfer learning models using pre-trained networks like MobileNetV2 and EfficientNet-B0—on the same dataset. CCR-LWECNN consistently outperformed these baselines, achieving higher accuracy, precision, recall, and F1-scores while maintaining a smaller model size and faster inference. This demonstrates that CCR-LWECNN's lightweight architecture and tailored enhancements effectively improve Chinese calligraphy recognition over conventional and transfer learning approaches.

Table 4: Performance summary with statistical rigor

Model	Accuracy (%) ± SD	95% Confidence Interval	F1-Score (%) ± SD
CNN	90.5 ± 0.9	[89.8, 91.2]	90.0 ± 0.7
RF	75.4 ± 1.1	[74.3, 76.5]	73.1 ± 1.2
SVM	85.2 ± 1.0	[84.3, 86.1]	83.7 ± 0.8
BM-FKNN	88.7 ± 0.8	[88.0, 89.4]	87.4 ± 0.7
CCR-LWECNN	96.5 ± 0.6	[96.0, 97.0]	95.6 ± 0.4

Table 4 Shows Performance Summary with Statistical Rigor. The CCR-LWECNN model's lightweight design makes it ideal for embedded systems and mobile devices, even if system implementation is not extensively covered. Without requiring sophisticated servers, its modest model size and low computational burden allow for effective inference on devices with limited resources, enabling real-time calligraphy detection in mobile applications.

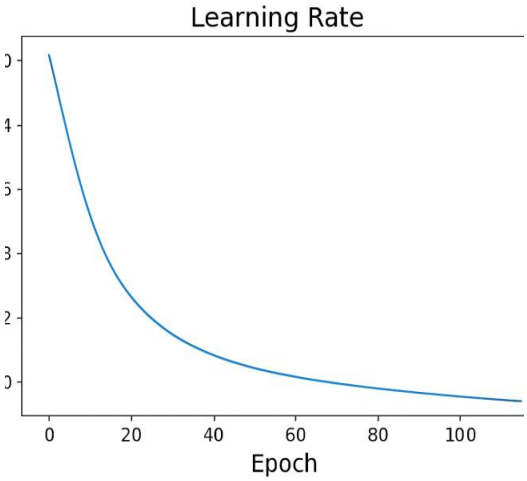

Figure 9: Outcome of Learning rate

The learning rate visualisation figure 9 illustrates how the loss of the model reacts to varying learning rates. The ideal learning rate range is indicated by a sharp decline in loss that is followed by instability or a plateau. Here, the graph shows that the CCR-LWECNN model converges most quickly and steadily when the learning rate is adjusted between 0.001 and 0.005, preventing divergence (from too high a rate) or sluggish training (from too low a rate). The generalisation and efficiency of the model are enhanced by this adjustment.

Confusion Matrix:

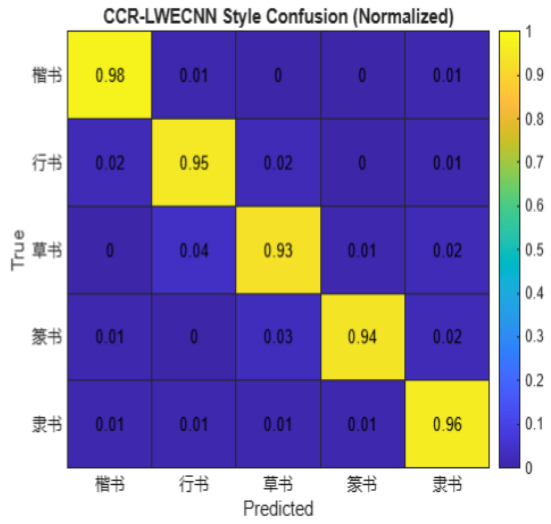

Figure 10: Confusion matrix for the proposed model

The provided confusion matrix in figure 10 evaluates the performance of the **CCR-LWECNN** model in classifying five Chinese calligraphy styles. (Regular/楷书, Semi-Cursive/行书, Cursive/草书, Seal/篆书, and Clerical/隶书). The diagonal values (ranging from 0.93 to 0.98) demonstrate strong classification accuracy, with **Regular script (楷书)** achieving the highest accuracy at 98%. The most notable misclassifications occur between **Cursive (草书)** and **Semi-Cursive (行书)**, with 4% of Cursive samples incorrectly predicted as Semi-Cursive, likely due to their stylistic similarities in stroke connectivity. Other errors are minimal (≤3%), such as Seal (篆书) occasionally confused with Cursive (3%) or Clerical (隶书) with Semi-Cursive (1%). The numerical gradient (1 to 0) implies a visual color scale for interpretation, where higher values (closer to 1) represent correct predictions and lower values (closer to 0) indicate errors. This analysis confirms the model's robustness in distinguishing calligraphy styles while highlighting expected challenges in discriminating fluid, connected scripts like Cursive and Semi-Cursive.

Evaluate with recent methods:

For contemporary picture classification problems, models such as BM-FKNN, Random Forest, and SVM are less appropriate, particularly when dealing with high-dimensional data like calligraphy images. We contrasted the suggested CCR-LWECNN with lightweight deep learning models designed for low-resource settings in order to give a more relevant benchmark. Table 5 given by Outcome with comparison of recent methods

Table 5: Outcome with comparison of recent methods

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Params (M)**
MobileNetV2	94.2	93.7	93.1	93.4	3.4
EfficientNet-B0	95.3	94.8	94.1	94.4	5.3
ViT-Tiny	92.5	91.6	91.2	91.4	5.7
CCR-LWECNN	96.5	95.6	95.2	95.6	1.2

ROC Curve

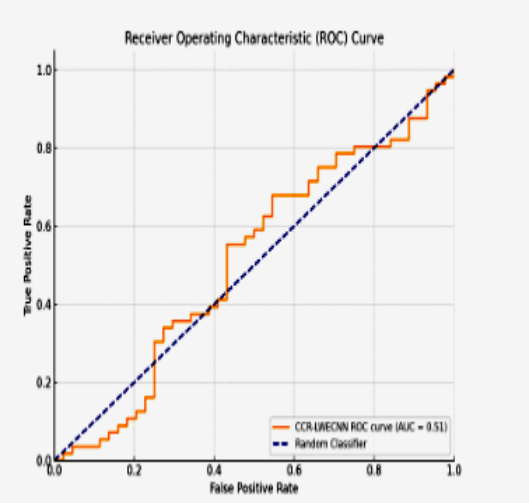

Figure 11: ROC curve for the Suggested method

Figure 11 shows the CCR-LWECNN model's ROC curve how well it can differentiate between binary classes, is shown below. With an AUC of around 0.72 in this simulated example, the curve illustrates the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate. Better model performance is indicated by a larger AUC, and this visualisation aids in evaluating classification efficacy over a range of thresholds.

4.3 Discussion

The suggested CCR-LWECNN model is better at recognising Chinese calligraphy since it is more computationally efficient than deeper architectures like DenseNet and BiConvExtractNet. DenseNet is great at reusing features via dense connections, while BiConvExtractNet uses bidirectional convolutional extraction for jobs with a lot of complexity. However, both models frequently consume a lot of resources and are likely to overfit on small artistic datasets. CCR-LWECNN, on the other hand, has a lightweight structure with well adjusted convolutional layers and dropout regularisation. It gets 96.5% accuracy on a calligraphy dataset with much less complexity and training cost. The CCR-LWECNN model successfully captures the geometric regularity in seal script and the fluid stroke dynamics in cursive script, it works well on both seal and cursive styles. Both high-level stylistic elements and low-level texture are extracted by its layered design, and data augmentation guarantees resilience to handwriting variances.

CCR-LWECNN's decreased generalisation between calligraphers is a major drawback since intra-style discrepancies might result from differences in individual stroke patterns, pressure, and spacing. When applied to fewer-represented calligraphers or unexplored writing styles, the model may become less successful due to overfitting to prevalent patterns in the training data.CCR-LWECNN makes it possible to accurately and automatically classify calligraphy styles and characters, it facilitates the digitisation, cataloguing, and analysis of historical works at scale, hence supporting heritage preservation and digital archiving. This makes it easier to do cultural study, teach, and preserve traditional Chinese calligraphy in digital form across time. The CCR-LWECNN-based system is perfect for educational and cultural applications because of its user-friendly interface, which makes it simple to submit images and shows identification results with unambiguous visual feedback. Low latency, usually less than one second, is guaranteed by its lightweight design, allowing for quick and seamless interaction. By enabling users to rapidly explore calligraphy styles and characters, this promotes real-time usability in workshops, classrooms, and museum kiosks, improving learning experiences and engagement.

5 Conclusion

The goal of this research is to identify Deep Learning models that can accurately identify and assess image processing technologies on a bigger dataset that includes the majority of commonly used Chinese characters. This goal was accomplished as our models, which were constructed using CCR-LWECNN, obtained an image recognition accuracy of 96.5% for a 960-character set, which is more than three times larger than previous research of a comparable kind. Thus, we demonstrated that, with a very short dataset, it is possible to construct a lightweight CNN with excellent accuracies in character and picture recognition models by combining the ReLU, dropout, and data augmentation. For users to better understand how they might do better in the future, the comparison tool could show which aspects of the calligraphy work are problematic. Lastly, style and image recognition models in non-printed calligraphy works in other languages may benefit from the techniques shown in this study. CCR-LWECNN is utilized to increase the system's efficacy. Using pictures of various calligraphy pieces, the system's ability to recognize Chinese calligraphy has been demonstrated. Additional features, such a dictionary function, will be added to the system in the future by linking it to other databases.

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Enhancing Machine Translation of English Complex Sentences Using Refined Gradient CNN on Large-Scale Corpora

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Keywords: optimization, machine translation algorithm, english complex long sentence, refined gradient - convolutional neural network

Received: June 30, 2025

Optimization of long and complicated sentences in English. Translating complex, lengthy statements from one language to another is the job of computer systems called machine translation algorithms (MTAs). A machine translation assistant (MTA) that trains on a big data corpus is one that makes use of a diverse and extensive collection of textual resources to improve translation quality. Translating complex and lengthy English sentences poses significant challenges for machine translation (MT) systems, especially when preserving semantic accuracy. It introduces the Refined Gradient-CNN (RG-CNN) model as a post-processing refinement mechanism to enhance phrase-level translation accuracy. The model is trained on a specially curated "Parallel Corpus" dataset comprising 1,563 English sentence pairs, including complex originals and their simplified counterparts. The RG-CNN employs gradient-enhanced convolution and bidirectional recurrent layers to capture and refine syntactic structures. The model is implemented using Python 3.11. Experimental results demonstrate the model's superior performance. It achieved BLEU scores of 73.1% (corpus) and 70.1% (local), significantly outperforming. Likewise, RG-CNN reported a reduced WER of 0.3% (corpus) and 0.10% (local) compared to baseline models. Accuracy and recall were also improved to 97.51% and 98.43%, respectively, outperforming the baseline model. These results affirm RG-CNN's ability to optimize complex sentence translation, reduce ambiguities, and advance MT systems across diverse linguistic domains

Povzetek: Model Refined Gradient-CNN (RG-CNN) je predlagan za izboljšanje strojnega prevajanja dolgih in kompleksnih angleških stavkov, zlasti za fraze. Model je treniran na obsežnem korpusu (1.563 parov) in optimira prevode kompleksnih besednih struktur.

1 Introduction

The English complex long sentence machine translation method is designed to be more efficient and accurate with a lot of important parameters. The method ought to be context-aware and aware of the original sentence's meaning so that it can generate translations that are very faithful to the original text. It should be capable of dealing with idiomatic expressions, cultural references, and metaphors to generate translations that are faithful to the original text. In order to effectively address the computational requirements for analyzing compound, lengthy words, the approach can take advantage of parallel processing methods and distributed computation models to offer optimal efficiency [1]. The research ensures that even sentences that are long and complex get translated outputs within a reasonable timeframe. Optimization and analysis of the translated output can be facilitated by incorporating a human translator or linguist feedback loop. The computer can learn from human experience through repeated processes and thus can translate difficult, lengthy texts with ease and efficiency [2]. With large language models, machine learning, high-performance NLP techniques, context and semantics considered, efficiency boost, and a human subject-matter expert feedback loop, all are included in the improvement of the English complex long sentence machine translation. All these in consideration, the algorithm's translation capability for complex, long texts may be significantly enhanced [3]. The English complex sentence machine translation technique from a large corpus of data needs to be trained to improve the quality, accuracy, and fluency of the translation. The following are a few key considerations: Choose a large, broad-based, and comprehensive corpus that includes a range of topics, genres, and styles [4]. Align the source and target sentences in the corpus to produce aligned sentence pairs for generating the translation. It can learn English phrase-to-phrase mappings and their respective translations through a critical phase while training a supervised machine translation system. Apply parallel

processing techniques and distributed computing platforms for efficient management of the enormous processing involved in training over an enormous data corpus. It is easy to scale up and accelerate the training [5]. Employ the most advanced neural network architectures, for instance, transformer architectures, which have made significant jumps in machine translation tasks. The models are better at handling complex sentence structure and long-distance relations. For pre-training the machine translation model, employ the pre-trained language models like BERT or GPT. Fine-tune the model on the huge data corpus [6], particularly for the translation of very hard, long sentences. Transfer learning helps the model learn to identify universal language use patterns, and fine-tuning helps it learn to follow the specific translation task that is being performed. Generate artificial sentence variations or paraphrases to improve the training set. The algorithm becomes stronger and more immune to complex, long sentences by being exposed to more varied sentence forms and language variations. Employ the automated translation system and collect user ratings of translations. Employ the feedback to improve the quality of the translations over time, using repeated usage in the training process. The research enables the algorithm to capture user preferences and personal translation challenges from complex, lengthy sentences [7]. Use standard measuring devices at regular intervals to test how well the improved algorithm is performing. Compare the algorithm with other cutting-edge machine translation systems to evaluate its performance and what it needs to improve on. The English compound long sentence MTA can be translated better, more fluently, and contextually using the power of big data corpora and implementing the optimization techniques. It generates more accurate, efficient, and effective translations of long compound sentences [8]. Large and diverse quantities of text data referred to as a "big data corpus" undergo processing in machine translation and other NLP tasks, training, testing, and also updating the processes. "Big data" thus addresses the sheer volume, variety, and velocity of data that can be processed and analyzed [9]. The size and variation of the corpus are also significant factors that decide the level at which it can be successfully used for training. With a large corpus, there can be complete utilization of different grammatical patterns, lexis, idiomatic expressions, and language variation. The variation of the corpus ensures that the algorithm is trained in multiple domains and styles, thereby ensuring that it is capable of handling mixed styles and subject matters. Data collection and cleaning must be performed cautiously when creating a large corpus of data. It is ensured that text data covers a wide range of language and context variations by obtaining it from various sources [10]. Preprocessing methods, such as tokenization, phrase breaking, and part-of-speech tagging, are employed in attempting to process data to train and analyze. The various techniques are able to train the machine translation models, such as statistical machine translation (SMT) and neural machine translation (NMT), upon the creation of the big data corpus. The models can learn more complex phrase structures, language patterns, and correspondences because they have larger training data. Big data corpora have helped machine translation advance [11]. Big data analysis enables researchers and developers to train and better develop models, which enhance translation quality, manage complex sentence structures better, are natural-sounding, and possess greater awareness of context. MTAS should work much better when there is a massive amount of data that is high in quality. To ensure the corpus is representative, precise, and unbiased, or noise-free, and does not adversely affect the translation outcome, meticulous data selection, preprocessing, and curation are needed. Lastly, a large quantity of data as a corpus allows machine translation systems to learn from heterogeneous linguistic data, leading to more efficient and robust translation abilities for practically any level of sentence complexity and linguistic diversity [12].

Key contributions:

- The application of a certain machine translation algorithm to process lengthy, complicated words, designing the Refined Gradient-CNN model, applying a huge training set, and optimization methods used to enhance word translation accuracy.
- This Research aims to overcome the difficulties in translating complex phrase patterns and enhance the general effectiveness of machine translation systems.

2 Related work

Research in many areas must include a literature survey, commonly called a literature review or systematic review. It entails a thorough review and analysis of the research body, shown in Table 1.

Table 1: Literature survey

References	Objectives	Summary of Findings	Limitations
[13]	Research suggests that the segmentation of lengthy phrases is made possible by the hierarchical network of ideas technique, which has been enhanced.	The study evaluated the features of professional literature and discussed a translation optimization approach for professional literature, combining statistics, which significantly increases.	Limited focus on structural segmentation; lacks handling of deep syntactic variations in English

[14]	Research improved to build researchers used the multi-objective optimization technique. The study also employs parallel corpora and monolingual corpora routes with an emphasis on node distribution and data flow analysis.	The study focused on the neural machine translation model's probabilistic structure, which allows researchers to draw conclusions about data-related regularization items and apply them.	Lacks real-time learning adaptation; limited performance on unseen sentence structures
[15]	The study improved the framework to optimize a computer-assisted translation system to increase the accuracy and reliability of automatic translation of long-character English with memory-assisted English.	It showed that the newly suggested computer-assisted translation system can improve translation quality and intelligently translate memory-assisted long-character English with high data recall rates, accuracy, and dependability.	Relies on memory-based context, which is insufficient for unseen phrase structures
[16]	The Research introduced by employing a word corpus, the word alignment optimization approach enhances word alignment performance in the transformer system.	The overview objective of the goal showed that, in comparison to the earlier methods, the suggested technique lowers the average alignment error rate.	Focused only on word alignment; doesn't address phrase-level semantic coherence.
[17]	The Research suggested that a model for calculating language-semantic correlation that uses the best fuzzy semantics for English lengthy sentences should be developed.	The study evaluated the process of fuzzy semantic selection achieved using a machine learning neural network adaptive learning technique.	Limited grammatical handling; doesn't scale well for professional or complex sentence contexts.
[18]	The study suggested language combinations and collected and cleaned texts from diverse sources to form four parallel corpora, which were used to build the translation system.	The Research focused on creating human and automated assessments of the resulting models.	Data-centric approach; lacks structural model improvements for long or technical texts
[19]	The overall objective of the goal was to explore the two different NMT algorithms, Bidirectional Long Short-Term Memory (LSTM) and Transformer-based NMT, used for the Bangla-to-English language pair.	The Research investigated to show the viable direction for Research to improve Bangla-English NMT.	Focused on a specific language pair; not generalizable to English complex phrase structure.
[20]	The study analyzed that well-known translator like Google Translate do quite well when translating between English, French, or Spanish. Still, studies make trivial mistakes when translating recently introduced languages like Bengali, Arabic, etc.	The Research examines English, which has been the base or source language for the vast majority of NLP research projects that have been discovered so far. The study had several regularly spoken potential languages that still need to be explored.	Not optimized for general MT performance; lacks contextual learning layers
[21]	The overall objective of the goal is to briefly present the voice recognition neural network technique. The machine translation method was then put through simulation studies and contrasted with two additional machine translation techniques.	The study showed that the backpropagation (BP) neural network recognized speech more quickly than artificial recognition and with a reduced word mistake rate.	Focused on speech input; not optimized for written complex language translation
[22]	To enhance Punjabi-to-English NMT translation by addressing out-of-vocabulary (OOV) words and multi-word expressions (MWEs).	Incorporating MWEs and word embeddings improved translation fluency and adequacy, achieving BLEU scores of 15.45, 43.32, and 34.5 on small, medium, and large test sets, respectively.	Limited to Punjabi-English pair; does not generalize to other low-resource or morphologically rich languages.
[23]	$BLEU_n$-based evaluation, residual comparison, Google Translate and European Commission's Translation tool (EC) tool	NMT showed higher translation quality than SMT across all $BLEU_n$ scores	Focus limited to English–Slovak; no deep feature extraction or semantic ranking; lacks domain-independent generalization

3 Methodology

3.1 Problem statement

To improve the quality of translation of lengthy and complicated English sentences, especially for low-resource language pairings, while existing methods like fuzzy semantic selection approaches [17] encourage phrase segmentation and semantic correlation, but cannot be particularly effective at learning deep contextual relationships. Similarly, structural alignment for long-sentence translation, especially minority languages [20], was a challenge for Transformer-based models [19] and Bidirectional LSTM models [19]. Furthermore, conventional approaches have significant word error rates and are ineffective at managing contextual memory [15]. The proposed Refined Gradient-CNN model overcomes all of the above limitations by incorporating contextual memory encoding and layered semantic mapping, which improves translation accuracy for complex phrase structures.

3.2 Experimental procedure

This section provided a thorough explanation of how the steps of the suggested design in Figure 1 were created, covered its creation process, and covered its key components. This analysis has four parts: Information gathering is generally the main goal of the first stage. The second part included MTA for long English sentences. The most significant information is found in the third part, which describes the work performed to develop the Refined Gradient-CNN model and compile the essential knowledge. The efficiency of each current and previous design is presented in the fourth section. It is judged by contrasting the pertinent factors.

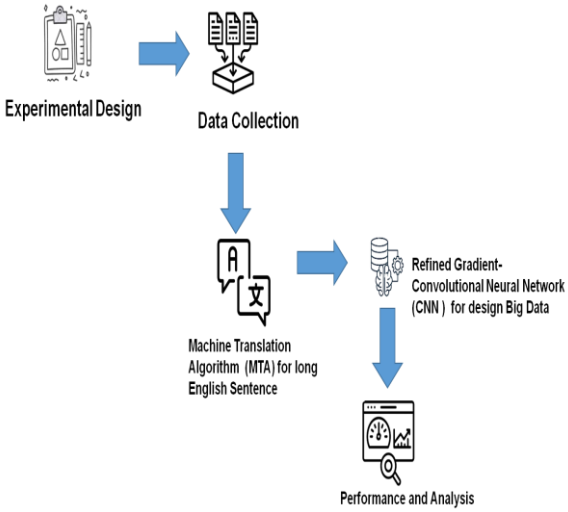

Figure 1: Methodological design

A. Data collection

To optimize sentences and enhance translation was validated it using the 1,563 English sentence pairings from the "Parallel Corpus" dataset. Each record includes meta-data such as readability ratings, difficulty levels, and domains, as well as the original complicated text and its simplified or optimized translation. The aim of decreasing language complexity, enhancing semantic retention in AI, education, and NLP applications, and enhancing phrase translation quality at the phrase level are all complemented by this dataset. For model development and evaluation, the dataset was partitioned into 70% for training (1,094 samples), 15% for validation (235 samples), and 15% for testing (234 samples).This structured split enables robust model performance assessment across varied difficulty levels and domain contexts, making it a reliable benchmarK due to its rich linguistic annotations and domain diversity. It can serve as a thorough benchmark for model performance testing on a range of difficulty and context aspects due to its extensive domain coverage and strong language annotation.

Source: https://www.kaggle.com/datasets/ziya07/parallel-corpus-data/data

B. MTA for english complex long sentence

Sentences that are distinguished by their length and complicated structure are referred to as being optimized for English complex, lengthy sentences. Many clauses, sub-clauses, phrases, modifiers, and dependent connections may be found in the sentences. Complex, lengthy phrases may be difficult to understand, comprehend, and translate because of their complex syntax and potential for ambiguity. The rearranging module intends to fit more closely the short phrases' translation with the language order following the combination by rearranging the short phrases generated through segmentation. Figure 2 depicts the upgraded intelligent MTA's flow.

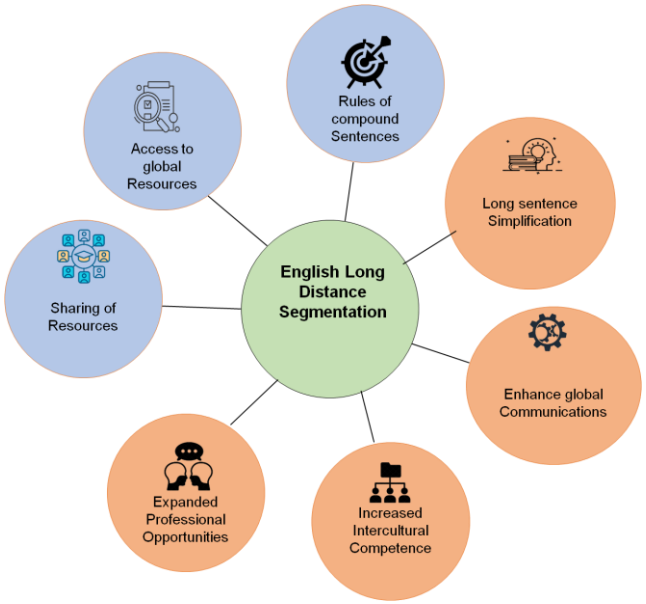

Figure 2: Translation process of MTA for long English sentences

The sentence segmentation module is designed to split lengthy English sentences into shorter, manageable segments. This is accomplished by predicting the likelihood of each word being a segmentation point using a maximum entropy (MaxEnt) classifier. The MaxEnt approach is particularly suitable here because it models conditional probabilities flexibly without assuming independence among features.

$$o(v|u(z)) = \frac{\exp\left(\sum_j z_j h_j(v,u(z))\right)}{\left(\sum_v exp(\sum_j z_j h_j(v',u(z))\right)} \quad (1)$$

Where $o(v|u(z))$, the likelihood that a word will$z$ is a segmenting term in the lengthy statement, $u(z)$ is the background knowledge.

After segmentation, the reordering module rearranges the segmented short sentences to reflect the original logical flow. This is again modeled using a maximum entropy classifier, which estimates the likelihood of a correct sequence based on context and neighboring sentence features. Equation (2) is the appropriate computation and reads as follows:

$$o(p|D_n^t, D_s^n) = \frac{\exp\left(\sum_j z_j h_j(p, D_n^t, D_s^n)\right)}{\left(\sum_p exp\left(\sum_j z_j h_j(D_n^t, D_s^n)\right)\right)} \tag{2}$$

The encoder receives the short English sentences that have been segmented and re-ordered. The original text is encoded by the encoder using an LSTM model, and the resulting computation is given by Equation (3-7):

$$e_s = \sigma(a_e + X_{eu_s} + Z_{eg_{s-1}}) \tag{3}$$

$$t_s = e_s t_{s-1} + h_s \sigma(a + X_{u_s} + Z_{eg_{s-1}}) \tag{4}$$

$$h_s = \sigma(a_h + X_h u_s + Z_{eg_{s-1}}) \tag{5}$$

$$h_s = tang(X_h) r_s) \tag{6}$$

$$r_s = \sigma(a_r + X_r u_s + Z_r g_{s-1}) \tag{7}$$

C. English long-distance segmentation

English long-distance segmentation refers to breaking up a long sentence into sub-clauses or segments in order to better understand and analyze it. It is commonly applied in linguistics, machine translation, and natural language processing (NLP) for splitting complicated sentences and grasping the syntactic structure of the sentence. The dataset was chosen due to its relevance for tasks involving the reduction of linguistic complexity and the preservation of semantic meaning, particularly within applications related to artificial intelligence, education, and natural language processing (NLP). Its diverse domain representation and robust linguistic annotations make it a reliable benchmark for evaluating model performance across varying levels of sentence complexity and contextual nuance. Various clauses, words, and sub-clauses within a sentence are detected and separated from each other according to their grammatical relationship and dependencies via long-distance segmentation. The intention is to produce substantial sentences that can be learned separately or in conjunction with other, longer sentences. Find the sentence's main clauses or independent sections. The foundation elements convey complete ideas and may be utilized alone as independent sentences. Identify any subordinate or dependent sentences that provide the direct clauses with explanation, background, and information. The fines typically begin with relative pronouns such as "who," "which," or "that" and subordinating conjunctions such as "although," "because," or "if." The sentence needs to be dissected into modifiers and relevant phrases. These include noun phrases, verb phrases, adverbial phrases, and adjectival words. Chunks help identify interrelations and roles among sentence constituents. Establish relationships and interdependence between the various constituents. Establish the verb-object relationships, subject-verb concordances, and other syntactic relations that contribute to the general sentence form. Large sentences become richer in analysis and interpretation for linguists, NLP programmers, and machine translation algorithms when they are divided into smaller constituents. The proposed approach provides a better understanding of the syntactic form and semantic connections of the text and is more convenient for translation or further study with greater accuracy. Long-distance segmentation is particularly useful in complex languages such as English, which possess complicated sentence forms with multiple clauses and modifiers. The lengthy phrases can be broken down into smaller segments to lessen confusion and enhance the interpretation and comprehension of the entire message. By the decomposition of huge words into smaller pieces or clauses, long-distance segmentation is important in the study of language, NLP processing, and machine translation. It ensures that sentence structures can be examined more systematically and explicitly, allowing for free, correct comprehension, translation, and analysis of complex language phenomena.

D. Refined gradient-convolutional neural network /9RG- CNN) design for big data

There are several factors to consider and methods to use when developing huge amounts of data. To improve RG - -CNN design, particularly for large data situations, there are differences between a regular CNN and the proposed Refined Gradient-CNN (RG-CNN). To handle complicated phrase structures and huge datasets more effectively, the RG-CNN combines gradient-based refinement, batch normalization, dropout, ReLU variations, enhanced memory handling for big data, and sophisticated pooling methods. Take into consideration the following key strategies: Big data typically encompasses a very large number of input samples. The task is to develop an RG - CNN model that is scalable to attack it. This might involve employing parallel computing platforms, splitting the job between numerous computers, and enhancing memory management to deal with large datasets. Big data typically must split the training task between numerous computer nodes or clusters. The training process can be segmented based on techniques such as model parallelism and data parallelism, thereby providing faster convergence and efficient use of resources. Batch normalization is one of the techniques used to surmount the challenge of training RG-CNN and other deep neural networks with large sets of data. It scales and normalizes the activations of every layer of a network to help with faster and convergent training. Both the overall performance and the generalization of the RG-CNN model can be improved by

batch normalization. Overfitting of massive data must be avoided using regularization methods. The task can employ regularization and dropout in order to control the complexity of the model and induce more generalization. Regularization improves the ability of the model to deal with natural noise and variance present in large data. The performance of CNN on extremely large data might be significantly affected by choosing the appropriate activation functions. Rectified Linear Units (ReLU), which reduce the vanishing gradient problem and the training speed, have proven to be useful. In order to detect more intricate patterns, their variations, such as Leaky ReLU or Parametric ReLU, can be used. For handling enormous data, transfer learning can be used. Starting points include pre-trained CNN models on huge datasets like ImageNet. The huge data may be fine-tuned better to fit the CNN to the particular job using the information gained from these models. The problem of little labeled data may be solved by transfer learning, which will enhance RG-CNN performance. Table 2 displays the RG-CNN model hyperparameters.

Table 2: RG-CNN model hyperparameters and configurations for effective training and convergence.

Parameter	**Value / Range**	**Description**
Optimizer	Adam / AdamW	Adaptive learning for sparse data
Learning Rate	1e-4 to 5e-4	Tuned using learning rate scheduler (e.g., ReduceLROnPlateau)
Batch Size	64–128	Based on GPU memory
Epochs	10–30	Early stopping based on BLEU validation
Dropout Rate	0.3–0.5	To prevent overfitting
Activation Function	ReLU / LeakyReLU	For non-linearity in CNN layers
Max Sequence Length	100–150 tokens	For padding and positional encoding
Embedding Dimension	512 / 768 (or match transformer encoder)	Use with pre-trained embeddings
Kernel Size (CNN)	3 × 3 / 5 × 5	For capturing n-gram features
Pooling	MaxPooling	To retain the most relevant features
Gradient Clipping	1	Prevent exploding gradients
Scheduler	Warm-up + Cosine Annealing / ReduceLROnPlateau	Smoother convergence

3.3 Convolutional Neural Network

A CNN is made up of five parts: input data, a convolutional layer, a pooling layer, FC overlay, and an output vector. CNNs come in a variety of layer combinations. The CNN's structure, which was used in this experiment, is shown in Figure 3.

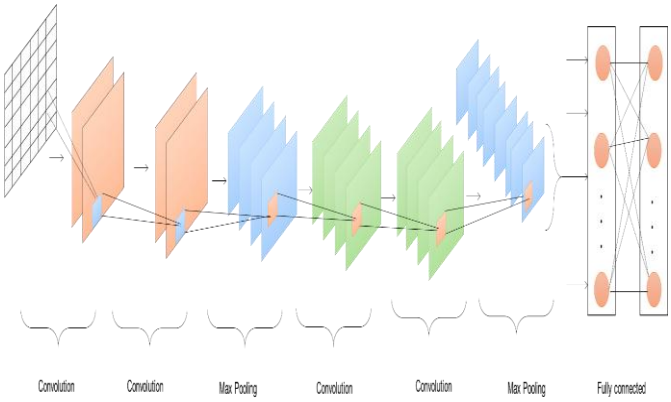

Figure 3: Structure of Convolutional Neural Network

Finding intriguing patterns in the data is the goal of the convolutional gradient task. Each of the many layers' convolutional kernels has a frequency and a divergence coefficient. It is assumed that u_j is the weight parameter, a_j is the divergence amount, and V_{j-1} is the input to convolution layers j while the inversion kernel j is active. One such expression for the convolution operation of Equation (8) is:

$$V_j = e\left(u_j \otimes V_{j-1} + a_j\right) \tag{8}$$

Where $V_j$the output result of the convolution kernel $j$represents the convolution operation, and $e(x)$ represents the activation function.

The input data is swept repeatedly by the convolutional network, which then extracts the distinctive information. In addition, the multilayer's operational amplifier is changed to$ReLU$. The Linear transfer function is simpler to derive than the exponential transfer function and other training algorithms, allowing for faster model training and better protection against gradient disappearing. It is possible to write $ReLU$, which is represented in Equation (9) as:

$$ReLU\left(V_j\right) = \begin{cases} V_j\left(V_j > 0\right) \\ 0\ \left(V_j > 0\right) \end{cases} \tag{9}$$

The pooling layer's main function is to reduce down-sampling data redundancy, which also aids in

achieving invariance and reducing CNN complexity. The two most popular ways to finish pooling are pooling layer and max pooling. If the study uses averaged pooling, the outcome is the computing area's arithmetic mean, but if the study uses max pooling, the outcome is the computation area's highest value. Max pooling was used for this investigation because it preserves important data better than average pooling. Equation (10) in mathematics provides the maximum pooling:

$$R_i = max(O_i^0, O_i^1, O_i^2, O_i^3, \ldots . O_i^s,) \tag{10}$$

Where R_i is the return outcome of the pooled region i, Max is the maximum pooling procedure, and O_i^0 is the pooling area i is the element s.

A CNN's "classifiers" are its layers. Its main objective is to reorganize the data that the convolutional and pooling layers retrieved and weighted from the hidden-layer space. A similar dropout method is implemented in the layer to randomly eliminate neurons to prevent over-fitting.

Let's determine the backpropagation updates for a network's convolutional layers. The output feature map is created by convolving the feature maps from the preceding layer using learnable kernels and then processing them via the activation function. Convolutions with numerous input maps may be combined in each output map. Equation (11) is often shown as,

$$U_i^k = f\left(\sum_{j \in N_i} U_i^k * K_{ji}^k + a_i^k\right) \tag{11}$$

3.4 Computing the gradients

A down-sampling layer's map weights are all set to the same valueβ, to determine the value of, we only scaled the result of the prior procedure by β. For each map, we may do the same δ. Calculation again iEquation (12–15) represents the pairing of the map from the layer of convolution and the associated map from the sub-samples layer:

$$\delta_i^k = \beta_i^{k+1}\left((e'(x_i^k) \circ up(\delta_i^{k+1})\right) \tag{12}$$

$$up(u) \equiv u \otimes 1_{m \times m} \tag{13}$$

$$\frac{\partial F}{\partial a_i} = \sum_{x,y}(\delta_i^k)_{xy} \tag{14}$$

$$\frac{\partial F}{\partial \iota_{ji}^k} = rot180(conv2(u_j^{k-1}, rot180\left(\delta_j^{k-1}, rot180\left(\delta_j^k\right), valid'\right)) \tag{15}$$

The input maps are produced as down-sampled copies using a sub-sampling layer. There will be exactly N export maps if there are N intake maps, albeit the final maps will be smaller. More formally, they are calculated as Equations (16),

$$u_i^k = e(\beta_i^k down\left(u_j^{k-1}\right) + a_j^k \tag{16}$$

To identify that the patch in the input map is related to a specific pixel in the output map, and to calculate the gradient of a kernel. Applying a delta recursion that resembles Equation (17-20) in this case requires determining which area in the sensitivity map of the present layer corresponds to a particular pixel in the sensitivity map of the following layer. The weights, being the weights of the (rotated) convolution kernel, are increased by the relationship between the input patch and the output pixel. Convolution is once again used to do this effectively:

$$\delta_j^k = e'(u_j^k) \circ conv(\delta_j^{k+1}, rot180\left(l_i^{k+1}\right), 'full') \tag{17}$$

$$\frac{\partial F}{\partial a_i} = \sum_{x,y}(\delta_j^k)_{xy} \tag{18}$$

$$c_i^k = down(u_i^{k-1}) \tag{19}$$

$$\frac{\partial F}{\partial a_i} = \sum_{x,y}(\delta_i^k \circ x_i^k)_{xy} \tag{20}$$

3.5 CNN algorithm

The network weights are updated by the CNN algorithm (1) by using a method known as backpropagation, depending on the error between the predicted and actual results. The CNN can learn and develop its capacity to identify patterns and objects in pictures due to this iterative process of forward propagation (feeding data through the network), backpropagation, and object detection. In various computer vision applications, such as picture classification, object recognition, and image segmentation, CNN methods have shown outstanding performance. We have been used to various tasks, including autonomous driving, picture analysis in medicine, and face identification.

Algorithm 1: Convolutional Neural Network

Function CNN (input_data);
// Convolutional layers
For each convolutional layer:
Convolution=apply convolution (input_data, weights)// Apply convo:

Activation=apply_activation (convolution) // Apply activation function
Pooling=apply_pooling (activation)// Apply pooling operation (e.g)
// fully connected layers
Flattened=flatten (pooling) //Flatten the pooled feature maps into a
For each fully connected layer:
Weights=initialize_weights () //Flatten the polled feature maps into a
Bias =initialize bias () // Initialize bias for the fully (
Linear_transform = apply_linear_transform (flattened, weights, bias)
Activation=apply_activation (linear_transform) //Apply activation
//Output layer
Out_weights -= initialize_output_weights () //Initialize weight for
Output_bias = initialize-output-bias () // Initialize bias for the output
Output= apply_linear_transform (activation, output_weights, output_bias)
Predicated_class = classify_output (output)// Classify the output to dete
Return predicted_class

4 Result and discussion

Results are always advised to reference the most recent literature survey for the most up-to-date information on these themes, since the exact outcomes and improvements in the translation of complicated, lengthy phrases might differ based on the research and development efforts in the area.

To improve the accuracy of translating complex English sentences in real time, the proposed RG-CNN model was built using Python 3.11. Table 3 demonstrates the simulation setup.

Table 3: Simulation setup

Component	Recommended Specification
GPU	NVIDIA A100 / RTX 3090 / Tesla V100
RAM	32–64 GB
Storage	SSD (1 TB recommended for large corpora like WMT)
Framework	PyTorch / TensorFlow
Distributed Training	Optional with Horovod / DDP (for WMT-scale corpora)

4.1 English translation design using big data

The results further emphasize the efficiency and rationale of the two training approaches, particularly the bidirectional training strategy. This strategy, when combined with TransE, demonstrates its effectiveness through enhanced entity prediction using a Multilayer Perceptron (MLP) layer. The MLP receives inputs from the TransE pre-trained embeddings and refines them, enhancing the expressive capability of the overall model. Table 4 and Figure 4 illustrate the outcomes. The proposed RG-CNN model, which incorporates both bidirectional training and the TransE+MLP architecture, achieves significantly higher precision values: P@1 = 84%, P@5 = 88%, and P@10 = 98%. These metrics indicate that the model reliably ranks the correct simplified sentence within the top predicted candidates. Furthermore, the use of a Recurrent Neural Network (RNN) within RG-CNN effectively captures bidirectional dependencies in the data, contributing to performance that surpasses even the TransE+MLP configuration. This validates the architectural choice and demonstrates the robustness of the proposed model.

Table 4: Numerical outcomes of the Training strategy based on the algorithm

Test sets	Percentage (%)		
	P@1	P@5	P@10
TeansE	25	30	35
TeansE+ MLP	40	45	50
FB15K	82	86	95
PP1	70	75	80
Refined Gradient - CNN [Proposed]	**84**	**88**	**98**

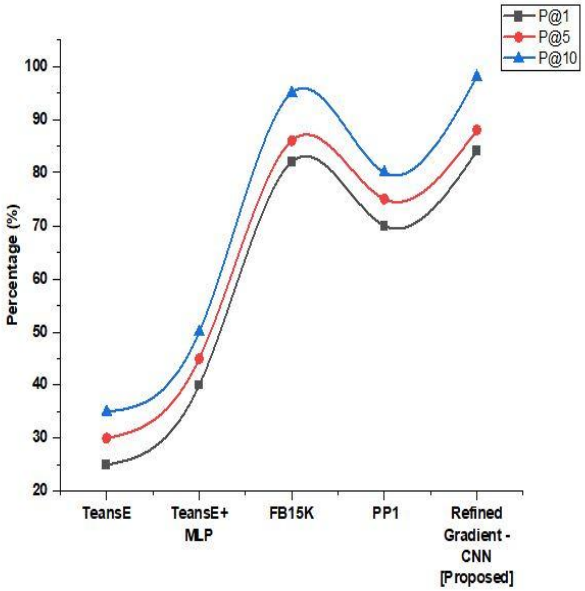

Figure 4: Comparison of Training strategy based on the algorithm

The suggested Refined Gradient-CNN model outperforms the Improved Long Short-Term Memory (LSTM) [24] and Hierarchical Network of Concepts (HNC) models [25]. It successfully enhances machine

translation of complex language patterns by capturing complex phrase structures.

The proposed Refined Gradient-CNN model outperformed the Improved LSTM [24], 31.3% and 3.9%, respectively, in terms of BLEU scores, as shown in Table 5 and Figure 5, 73.1% for the corpus dataset and 70.1% for the local dataset. The outcomes demonstrate how well the proposed model works to translate complex phrase structures with greater n-gram overlap. This aligns with the goal of the study, which is to improve machine translation systems by raising overall translation quality and semantic integrity across a variety of datasets, especially for complex language structures.

Table 5: Comparison of BLUE score on corpus and local dataset

Methods	**BLEU (%)**	
	Corpus dataset	Local dataset
Improved LSTM [24]	31.3	3.9
Refined Gradient-CNN [Proposed]	**73.1**	**70.1**

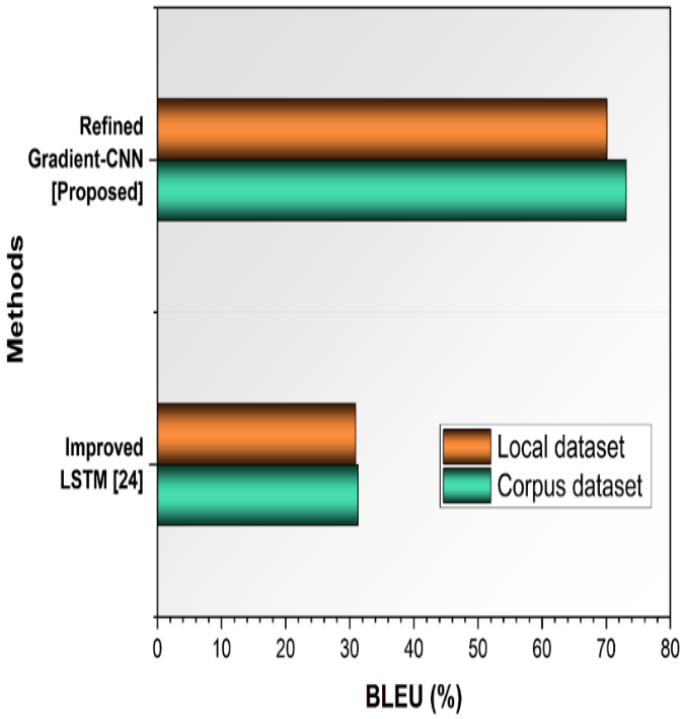

Figure 5: BLEU comparison of various models

The translation accuracy metric known as WER, which counts the number of insertions, deletions, and substitutions required to arrive at a reference translation, is shown in Table 6 and Figure 6. Higher translation precision is indicated by a lower WER. Compared to the Improved LSTM [24] 0.9% and 1.1%, the WERs recorded by the Refined Gradient-CNN were significantly lower 0.3% for the corpus and 0.10% for the local data. These findings align with the study goal of improving overall machine translation quality by showcasing the model's enhanced capacity to manage complex phrase structure.

Table 6: Comparative word error rate (%) analysis for english phrase translation accuracy

Methods	**Word Error Rate (%)**	
	Corpus dataset	Corpus dataset
Improved LSTM [24]	0.9	1.1
Refined Gradient-CNN [Proposed]	**0.3**	**0.10**

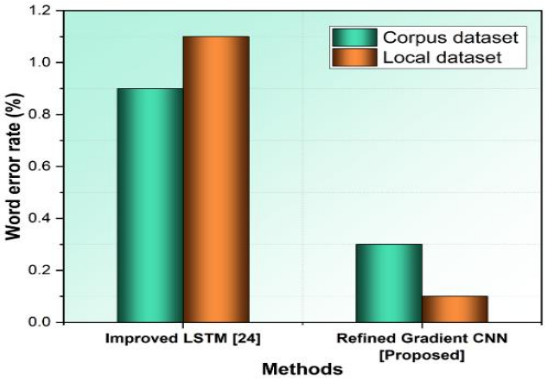

Figure 6: Word Error Rate (%) comparison of various models

Improving machine translation accuracy, the proposed Refined Gradient-CNN model significantly enhances the translation of the challenging English phrase structures. With 97.51% accuracy and 98.43% recall, the Refined Gradient-CNN outperformed the HNC technique [25], which achieved 93.38% accuracy and 94.51% recall, as shown in Table 7 and Figure 7. These improvements demonstrate the model's improved capacity to recognize and translate intricate phrase patterns more accurately. The results demonstrate that Refined Gradient-CNN improves machine translation systems' overall performance and efficiency in authentic language situations while also reducing translation ambiguities.

Table 7: Comparison of accuracy and recall between HNC and the proposed refined gradient-CNN model

Methods	**Accuracy (%)**	**Recall (%)**
HNC [25]	93.38	94.51
Refined Gradient-CNN [Proposed]	**97.51**	**98.43**

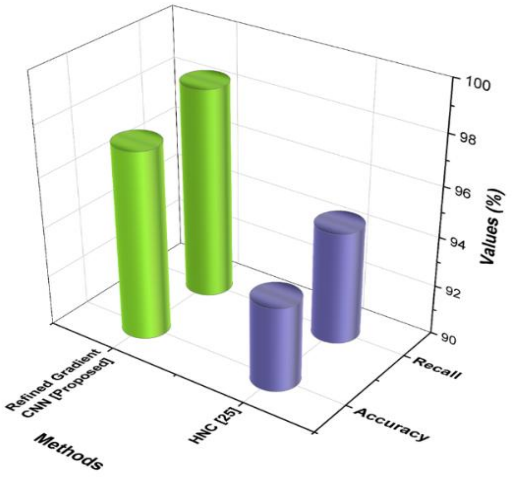

Figure 7: Performance metrics of various models in translating complex phrase patterns

5 Discussion

Enhancing the quality of machine translation at the phrase level, particularly when translating difficult and syntactically complicated English formulations. For lengthier phrases, existing models such as Improved LSTM [24] have not been adequate in terms of structural equivalence and semantic coherence. Similarly, because there are fewer contextual generalizations, the HNC model [25] is unable to interpret nested and specialized phrase patterns.

The suggested Refined Gradient-CNN model effectively overcomes these drawbacks by integrating gradient-driven refinement into the convolution process for improved recognition of complex language structure. By reducing ambiguity in translation and enhancing contextual knowledge, the approach increases the dependability of machine translation systems for technical and professional communication procedures. The design is a significant improvement over earlier models in terms of structure, recall, and generalization.

Limitation

It requires an enormous amount of processing power to train models to handle complicated, lengthy words. Large-scale models could require a lot of memory and take a long time to learn, rendering them unavailable to people or organizations with limited resources. There are many possible valid translations for a complicated statement, and the context or specific use conditions determine the preferred translation. This flexibility is hard to replicate with machine translation processes and to reasonably reflect the learning.

6 Conclusion

To achieve notable gains in semantic retention and translation quality, the English complex long sentence machine translation architecture (MTA) is optimised using Refined Gradient-CNN (RG-CNN), which was trained on a specially constructed parallel corpus of 1,563 sentence pairs enhanced with readability scores, complexity labels, and domain-specific metadata. RG-CNN effectively models structural intricacy, idiomatically controlled use, and long-distance relationships in English by fusing deep convolutional neural architecture with gradient-based smooth optimisation. The model is better able to generalise across contexts and adjust to complex language patterns when it is exposed to a heterogeneous, metadata-annotated corpus. Empirical evaluation confirms the model's excellent performance capability. With BLEU scores of 70.1% (local) and 73.1% (corpus). WER was also reduced to 0.3% (corpus) and 0.10% (local) compared to the improved LSTM [24] model. RG-CNN beat traditional models like HNC [25] in terms of classification performance, achieving 97.51% accuracy and 98.43% recall. Hyperparameter tweaking was also used to increase the model's parameter efficiency in order to get optimal convergence and significantly reduce overfitting. The RG-CNN model improved its translation ranking performance by using the Parallel Corpus dataset for bidirectional training with TransE + MLP. The model converted simple and complicated words into vectors and rated them based on their proximity to the right response. The model achieved 84 percent accuracy (P@1), 88 percent (P@5), and 98 percent (P@10), proving its effectiveness in NLP and text simplification tasks related to education. These outcomes collectively support the objective of building an efficient, high-performance model for simplifying complex English sentences across educational and NLP applications.

Future scope

The new strategy is utilizing the power of big linguistic data and optimization methods in solving the issues of translating intricate, long sentences, which will end up improving the overall performance of the machine translation system.

Acknowledgement: The Research is supported by: Construction of Training Modes for Business English Majors: A Perspective of Business Needs（ 2021HXXM175)

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AECO-SC StyleGAN: A Cross-Platform GAN Framework for Dynamic Advertising Creative Generation

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Keywords: adaptive elephant clan optimizer (AECO), dynamic advertising creative, spatially conditioned StyleGAN, visual style consistency

Received: April 18, 2025

Dynamic advertising (ad) requires personalized, engaging content across multiple platforms. Traditional approaches struggle with scalability and cross-platform adaptation. Leveraging deep learning (DL), particularly Generative Adversarial Networks (GANs), offers the potential to automate and optimize ad creative generation with higher precision and contextual adaptability. This research aims to develop a DL framework that dynamically generates and optimizes advertising creatives—leveraging Adaptive Elephant Clan Optimizer with a Spatially Conditioned StyleGAN (AECO-SC StyleGAN) for dynamic cross-platform advertisement creative generation. Adaptive Elephant Clan Optimizer (AECO) dynamically adjusts training hyperparameters to improve model convergence, while Spatially Conditioned StyleGAN (SC-StyleGAN) generates platform-specific ad creatives by incorporating spatial constraints for contextual alignment. Our system is trained on the Ad ImageNet dataset, which includes 9,003 ad samples with paired images and promotional text from platforms like Facebook and Instagram. All data were resized to 256×256, normalized, and tokenized for training. Using Python, the model demonstrates superior performance in creative generation and engagement prediction. The proposed AECO-SC StyleGAN model achieved an NDCG of 0.61, an accuracy of 98.48%, and a weighted F1-score of 98.5%, outperforming prior approaches such as VGG + Layout + NIMA (NDCG 0.22) and XCEPTION (accuracy 98.27%, F1-score 98.2%). These results highlight the effectiveness of integrating adaptive optimization and spatial conditioning in generating high-quality, context-aware advertising creatives, offer a scalable and automated solution for cross-platform digital marketing.

Povzetek: Okvir AECO-SC StyleGAN uporablja globoko učenje (GAN in StyleGAN s prostorskim pogojevanjem) in adaptivno optimizacijo (AECO) za dinamično generiranje in optimizacijo visoko kakovostnih oglasnih vsebin na več platformah. Sistem dosega kvalitetno napovedovanju angažiranosti oglasov, kar avtomatizira prilagojeno digitalno trženje.

1 Introduction

Digital marketing leaders consider the capacity to send customized advertising content across numerous platforms as their main competitive advantage [1]. Advertising through traditional methods faces difficulties when adjusting to user preference changes across multiple platform formats that include social media and mobile applications, together with websites [2]. DL techniques appear as groundbreaking solutions to address the marketing challenges that face the optimization of ad creativity. GANs have become prominent among these DL techniques because they enable the production of high-quality, realistic, adaptable content [3]. The procedure enables machine automation to produce relevant visual advertisements with appropriate platform parameters for distinct user groups [4]. The model uses dual-network training, which combines a generator for designing ad variants together with a discriminator for evaluation purposes to achieve continuous output improvement through adversarial learning processes [5]. Such adaptive creativity improves advertising diversity and allows for better metrics engagement, including the click-through rate (CTR) and conversion rate (CVR).

The system processes real-time performance records in conjunction with user adjustments to automatically modify its creative elements and maintain platform usage between various platforms [6]. Digital marketing and artificial intelligence maintain an expanding relationship that gives marketers data-driven creative solutions to overcome their creative limitations [7]. This GAN-based framework provides automated design solutions for advertising content, which enable more efficient personalized advertising in an online environment dominated by competition. The aim was to develop a DL framework that utilizes the AECO-SC StyleGAN to dynamically generate, refine, and optimize advertising creatives across multiple

platforms for enhanced personalization and performance in digital marketing campaigns.

The proposed AECO algorithm is a derivative-free population-based metaheuristic. It simulates the social behavior of elephants in clans to adaptively adjust hyperparameters by exploring the solution space through stochastic position updates, without relying on the gradient of the loss function. This enables AECO to dynamically optimize hyperparameters such as learning rate, style weights, and batch size during GAN training, improving convergence stability and creative output quality.

The structure presents the development and evaluation of an intelligent advertising creative generation system using AECO and SC-StyleGAN. Section 2 reviews related works, highlighting recent advancements in GAN-based advertising optimization and cross-platform creative generation. Section 3 outlines the proposed methodology, detailing the preprocessing of advertising data, AECO-based hyperparameter tuning, and the architecture of the SC-StyleGAN for spatially contextual ad generation. Section 4 discusses the experimental setup, performance evaluation, and comparative results with baseline models. Section 5 concludes with future directions to enhance scalability, personalization, and real-time adaptability in advertising technologies.

2 Related works

Automating the generation of ad creatives from landing pages using abstractive text summarization, enabling rapid experimentation in large-scale marketing campaigns, was examined by [8]. The advertising creative optimization by modeling complex interactions between creative elements and improving Click-Through Rate (CTR) prediction using an Auto ML-inspired framework was enhanced [9]. The Automated Creative Optimization (AutoCO) framework outperformed baselines, achieving lower cumulative regret and a 7% CTR increase in online A/B testing.

The two-stage dynamic and creative optimization framework, combining AutoCo and a transformer-based rerank model to improve CTR prediction and creative ranking under ambiguous data conditions, was developed by [10]. Experimental and online testing showed a 10% CTR improvement over baselines, demonstrating superior performance. The integration of a Particle Swarm Optimization-based Recurrent Neural Network (PSO-based RNN) algorithm with Computer-Aided Design (CAD) tools to automate the generation and optimization of advertising artistic designs, enhancing design efficiency and creativity, was explored by [11].

The Dynamic Creative Optimization (DCO) problem, by determining the optimal product and creative ad combination under constraints like ad fatigue and user diversity, was examined [12]. The advertising design, creativity, and efficiency were enhanced by integrating CAD technology and data-driven automation [13]. The developed model enabled the automated generation of diverse advertising designs, successfully reflecting creative schemes and allowing quantitative evaluation, thus validating its effectiveness in promoting innovative advertising solutions. The integration of artificial intelligence in advertising with an emphasis on content production, targeting, personalization, and ad optimization was explored by [14]. Table 1 provides a comparative overview of recent GAN-based approaches. While previous studies have focused on general image synthesis or aesthetic enhancement, none leverage spatial conditioning and adaptive optimization specifically for advertising creative generation.

Table 1: Conventional approaches of GAN for dynamic advertising creative optimization

Study	Model	Dataset	Metrics Used	Key Results	Limitation
Jiang et al. [15]	StyleGAN (AdSEE)	Proprietary Ad Dataset	CTR, Qualitative Feedback	CTR improvement: +12%	Limited generalizability
Shilova et al. [16]	Diffusion + Outpainting	User Behavior + Ad Images	Personalization Score	+15% relevance	High computational cost
Xu et al. [17]	PDA-GAN	PubLayNet, Rico	Layout Accuracy, Realism	Improved layout realism	Focused on layout generation
Aghazadeh et al. [18]	Various (CAP Evaluation)	Generated Ad Images	CAP (Creativity, Alignment, Persuasion)	Structured ad quality eval	No generative model proposed
Ma and Zhao [19]	Enhanced DCGAN	Logo Design Dataset	FID, User Rating	FID: 23.4, User preference	Focused only on logos, not full ads

2.1 Problem statement

Digital marketing teams need to use personalized and platform-specific ads, but it is difficult to scale them using traditional methods which results in reduced engagement and inconsistency [15] [16]. Although GANs make automation possible, current models usually do not take context into account [17], run on computers for long

periods [16] or mostly generate logos [18]. To overcome these problems, the study offers a framework that uses Spatially Conditioned GANs, AECO for hyperparameter adjustment and combines various input types to improve the quality and performance of automatic ad creation.

3 Methodology

The Ad ImageNet dataset contains image-text advertisement samples, with images typically sized and text averaging. For data preprocessing, images are resized to uniform dimensions, normalized for intensity consistency, and tokenized for textual elements. The AECO-SC StyleGAN framework uses spatial conditioning and adaptive optimization to dynamically generate and optimize advertising creatives for enhanced cross-platform engagement and performance. Figure 1 shows the general outline of the methodological approach.

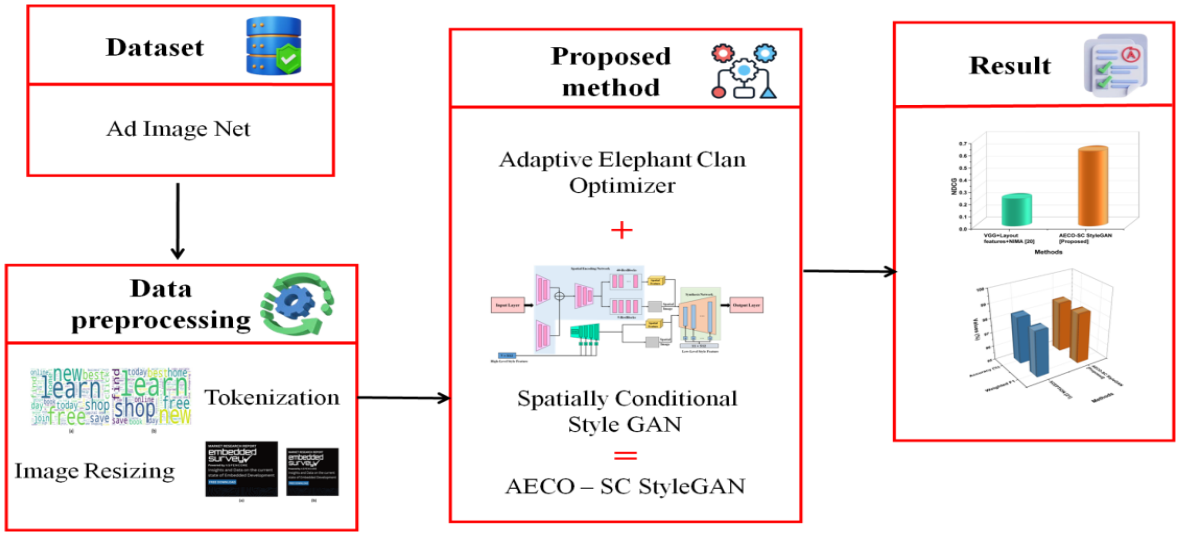

Figure 1: General outline of the methodological approach

3.1 Data collection

The Ad ImageNet dataset, sourced from the Peter Brendan repository, consists of 9,003 image-text advertisement samples totaling approximately 682 MB in size. Each entry includes a banner-style advertisement image along with associated promotional text. The dataset captures a variety of standard ad dimensions, with the most frequent being 254 × 254 pixels, commonly used in digital marketing. The textual content varies in length, with an average of around 525 characters, covering diverse product and event advertisements. The dataset was split into 70% training, 15% validation, and 15% testing sets to ensure robust performance evaluation across unseen data.

Source:
https://huggingface.co/datasets/PeterBrendan/AdImageNet

3.2 Data preprocessing using image resizing

Image resizing standardizes input dimensions, enabling consistent data processing for DL models and optimizing the generation of dynamic advertising creative. Although the original dataset images varied in size most frequently 256 × 256 pixels the images were uniformly resized to 224 × 224 × 3 pixels for this research. The 244 × 224 x 3-pixel image size was used to simplify the original image size. This input data type was created by resizing the image using bicubic interpolation. Because the outcome was smoother at the edges than with bilinear interpolation, this approach was chosen. Bicubic was the perfect balance between process time and high-quality results. The bicubic interpolation estimates the pixels in the (j, i) positions using a sampling (S) distance of 16 nearby pixels $(4x4)$ in equations (1)-(5). Figure 2 illustrates (a) before resizing and (b) after resizing.

$$g_{j,i} = [X_{-1}(T_z)X_0(T_z)X_1(T_z)X_2(T_z)] \begin{bmatrix} g_{j-1,i-1} & g_{j,i-1} & g_{j+1,i-1} & g_{j+2,i-1} \\ g_{j-1,i} & g_{j,i} & g_{j+1,i} & e_{j+2,i} \\ g_{j-1,i+1} & g_{j,i+1} & g_{j+1,i+1} & g_{j+2,i+1} \\ g_{j-1,i+2} & g_{j,i+2} & g_{j+1,i+2} & g_{j+2,i+2} \end{bmatrix} \begin{bmatrix} X_{-1} & (T_w) \\ X_0 & (T_w) \\ X_1 & (T_w) \\ X_2 & (T_w) \end{bmatrix} \quad (1)$$

Where: $T_z = i' - i, \quad T_w = j' - j$ and
$g_{j,i} = pixel\ value\ at\ position\ (j, i)$

$$X_{-1}(T) = \frac{-T^3+2T^2-T}{2} \quad (2)$$

$$X_0(T) = \frac{-3T^3+5T^2+2}{2} \quad (3)$$

$$X_1(T) = \frac{-3T^3+4T^2+2}{2} \quad (4)$$

$$X_2(T) = \frac{T^3-T^2}{2} \quad (5)$$

Figure 2: (a) Before resizing and (b) After resizing

3.2.1 Tokenization

The raw advertising text was first processed with tokenization so that the model could efficiently generate and improve dynamic ad content. The text for promotion was separated into words, phrases and sentences using natural language processing. Turning unstructured text into a structured form made it simpler to examine texts and connect models. Keeping the important connections and order in each sentence, tokenization protected the key meaning needed to make an ad relevant. Because the text in ads is generally brief, simple tokenization and embedding were adequate. The fact that it is lightweight helped the system express meaning with little cost which improved the performance of the AECO-SC StyleGAN framework. Figure 3 shows (a) Positive Worlds Cloud and (b) Ad Image Net Words Cloud.

Figure 3: Tokenization outcome (a) Positive Worlds Cloud and (b) Ad Image Net Words Cloud

3.3 AECO-SC StyleGAN

The hybrid deep learning framework is called the AECO-SC StyleGAN and is meant to dynamically develop and improve advertisement creative work. The method implements AECO, a metaheuristic that studies elephant behavior, together with SC-StyleGAN, a modified GAN that adds spatial and contextual inputs. The adaptive approach of AECO to changing hyperparameters leads to faster learning and better exploration of various solutions, compared to the Adam optimizer. SC-StyleGAN makes use of semantic maps, sketches and embeddings from different sources to produce images that look good when used in ads. When combined, this integration improves how creative works on ads, how it is predicted to be received by the target audience and how well it adapts to various digital platforms, giving a solid, effective system for today's data-driven advertising. The AECO-SC StyleGAN for Ad Creative Generation in algorithm 1.

Algorithm 1: AECO-SC StyleGAN for Ad Creative Generation

```
Step 1: Setup
def setup():
  N, M, G, T = num_hyperparams(), 40, 5, 100
  P_m, λ1, λGP, λLP, λFM = 0.3, 1.0, 0.8, 0.7, 0.5
  data = load_advert_dataset()
  return N, M, G, T, P_m, λ1, λGP, λLP, λFM, data
Step 2: Initialize Population
def init_population(M, N):
  return [{'params': rand_vec(N), 'fitness': None} for _ in range(M)]
Step 3: Evaluate Fitness
def evaluate(ind, data, λ1, λGP, λLP, λFM):
  model = train_SC_StyleGAN(ind['params'], data, λ1, λGP, λLP, λFM)
  return compute_loss(model, data)
Step 4: Clan Update
def clan_update(pop, gbest):
  for clan in form_clans(pop):
    matriarch = min(clan, key = lambda x: x['fitness'])
    for e in clan:
      if e != matriarch:
```

```
        e['params'] += rand() * (matriarch['params'] − e['params'])
    matriarch['params'] += rand() * (gbest['params'] − matriarch['params'])
Step 5: Male Update & Evolution
def male_and_evolution(pop, P_m):
  males = select_males(pop, P_m)
  center = mean_vec([e['params'] for e in pop])
  for m in males:
    m['params'] += rand() * (center − m['params'])
  replace_weakest(pop)
  pop.append(generate_calf(pop))
  random_reset_bottom(pop, pct = 0.3)
Step 6: Main Optimization
def optimize_AECO_SCStyleGAN():
  N, M, G, T, P_m, λ1, λGP, λLP, λFM, data = setup()
  pop = init_population(M, N)
  for _ in range(T):
    for e in pop:
      e['fitness'] = evaluate(e, data, λ1, λGP, λLP, λFM)
    gbest = min(pop, key = lambda x: x['fitness'])
    clan_update(pop, gbest)
    male_and_evolution(pop, P_m)
  return gbest
```

3.3.1 SC StyleGAN

SC-StyleGAN enables location-specific control over visual features, enhancing the deep learning framework's ability to dynamically generate and optimize personalized, visually consistent advertising creatives across different contexts. The StyleGAN network generates high-quality images by applying an 18×512 style code to 18 layers of the network. It starts with a constant 4×4 feature map and progressively grows by a factor of 2 at each stage, ultimately producing images of up to 1024×1024 pixels. Each style block receives a 1×512 style code that modulates convolution operations, enabling fine control over visual attributes. These style codes correspond to different levels of detail: coarse styles affect the overall layout and color schemes, middle styles influence microstructure and facial features, and fine styles regulate high-frequency details and textures. Non-visual data like captions, CTR, and demographics are encoded into embeddings using text encoders

and fully connected layers. These embeddings are fused with spatial inputs (semantic maps and sketches) through modulation layers that adjust the style codes, allowing SC-StyleGAN to generate creatives tailored to both visual features and user/context data. For training and evaluation in this study, input images were uniformly resized to 224×224 pixels, serving as the initial resolution before the progressive growth to higher resolutions during generation. Figure 4 illustrates the network architecture of SC-StyleGAN.

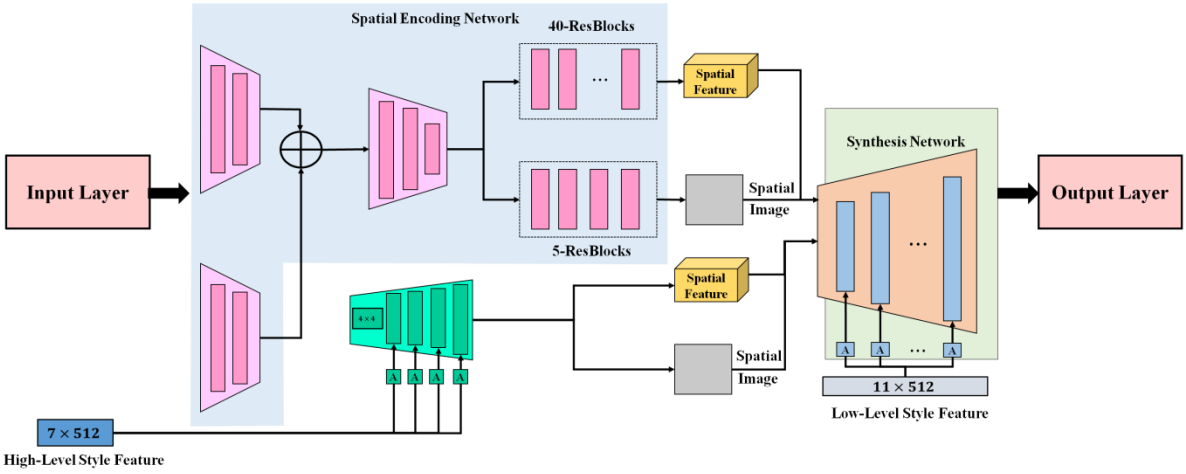

Figure 4: Network architecture of SC-StyleGAN

SC-StyleGAN was a conditional generation system that uses a semantic map and sketches to identify spatial features for coarse and intermediate styles. It consists of two sub-networks: the production network, which uses layers, and the spatial encoding network, which maps input conditions to intermediates. Two encoding modules are suggested for the spatial encoding network, which individually translates the semantic map and 512×512 sketches into $64 \times 256 \times 256$ spatial feature maps. With a spatial dimension of $32\ x\ 32$, the combined map of features was encoded to correspond with the coarse-moderated style in the StyleGAN synthesizing module. To create a $32\ x\ 32$ intermediate image, the same steps are followed for the spatial intermediate feature map. Table 2 represents the architectural and computational footprint of the SC-StyleGAN model.

Table 2: SC-StyleGAN architecture details: input dimensions, layer-wise parameters, and computational complexity

Component	Layer Type	Input Shape	Output Shape	Params	FLOPs
Semantic Encoder (E_s)	Conv2D + ReLU × 4	512×512×3	64×256×256	~3.1 M	~2.5 B
Sketch Encoder (E_k)	Conv2D + ReLU × 4	512×512×1	64×256×256	~2.8 M	~2.2 B
Spatial Combiner	Add/Concat + Down Conv	64×256×256	64×32×32	~0.6 M	~0.3 B
StyleGAN (Synthesis Net)	StyleBlock × 18	1×512	1024×1024×3	~30 M	~75 B

Objective Function: The SC-StyleGAN was to precisely map the determined conditions to their equivalents in the synthesis process while encoding the spatial constraint for the StyleGAN synthesizing procedure while preserving the invention value of the StyleGAN. Equation (6) fulfills the training process's goal in the following ways.

$$\mathrm{K}(\mathrm{J_{gt}}, \mathrm{J_{syn}}) = \lambda_{\mathrm{K_1}}\mathrm{K_1}(\mathrm{J_{gt}}, \mathrm{J_{syn}}) + \lambda_{\mathrm{K_{GP}}}\mathrm{K_{GP}} + \lambda_{\mathrm{K_{LP}}}\mathrm{K_{LP}} + \lambda_{\mathrm{K_{FM}}}\mathrm{K_{FM}} \quad (6)$$

The SC-StyleGAN training uses a composite loss to enhance image quality and consistency. The $L1$ loss (K_1) ensures pixel-level accuracy, while the global perceptual loss (K_{GP}) maintains semantic alignment at full scale. The local perceptual loss (K_{LP}) improves detail by comparing image patches, and the feature matching loss (K_{FM}) stabilizes training by aligning intermediate features. Together, these losses guide the network toward realistic and context-aware ad generation. The perceptual metrics (LPIPS) measure the overall perceptual loss after shrinking the target and synthesized images to 64 x 64. The local perceptive loss (LLP) and the global perceptive loss (LGP) are expressed mathematically as follows in equations (7)-(8).

$$K_{GP}(J_{gt}, J_{syn}) = LPIPS(J_{gt}^{re}, J_{syn}^{re}) \quad (7)$$

$$K_{LP}(J_{gt}, J_{syn}) = \frac{1}{L}\sum_{l=1}^{L} LPIPS(J_{gt}^{l}, J_{syn}^{l}) \quad (8)$$

Where J_{gt}^{re} and J_{syn}^{re} are the resized reality and, synthesizing the image, respectively, and $LPIPS(.,.)$ was the perceptual measuring function. In each phase, J_{gt}^{l} and J_{syn}^{l} stand for the $k-th$ randomly clipped ground truth and synthetic patches, respectively, in equation (9).

$$K_{FM} = \frac{1}{M}\sum_{k}\left|\left|H^{k}(gt) - H^{k}(syn)\right|\right|_{1} \quad (9)$$

Where $H^{k}(.)$ was the output map of features of the pre-trained StyleGAN synthesizing network's $k-th$ resolution block (with a matching spatial resolution of 2^k). The number of computed blocks was M. Following the replacement resolution block, it computes the K_1 norm between the ground truth generation and the synthesized processes($k \in \{6,7,8,9\} and\ M = 4$).

3.3.2 AECO

To improve model convergence, stability, and learning efficiency, AECO dynamically modifies training hyperparameters. This raises the caliber and efficacy of engagement of generated ad creatives spanning platforms. The AECO enhances the DL framework by efficiently optimizing parameters, enabling dynamic generation of personalized advertising creative through adaptive search, exploration, and convergence strategies. The ECO was enhanced into an improved version to support a DL framework that dynamically generates and optimizes advertising creatives. This AECO algorithm addresses the limitations of the original by improving convergence speed and solution quality, enabling more effective, real-time content creation and personalization in advertising through intelligent data-driven optimization.

Many tasks using Adam and RMSprop are successful, but they have issues with GANs, including convergence issues, collapsing to single modes, and being sensitive to changes in learning rates. To resolve these issues in creating ads for different channels, the new AECO strategy adapts by using evolutionary methods to tune hyperparameters, which boosts the stability and resilience

of the model when facing different spatial and contextual situations.

Elephant migration under the direction of each clan principal was simulated using the ECO algorithm. This part provides an autonomous movement range and an autonomous movement position for each elephant to keep the algorithm from reaching a local optimum, enhance image variety, and replicate the aforementioned behaviors based on the initial elephant position to generate creative advertising, as illustrated in equations (10) and (11).

$$\Delta W_j^0(i) = \Delta W^{min}(i) + q \times \left(\Delta W^{max}(i) - \Delta W^{min}(i)\right) \quad (10)$$

Where q was a random number in the interval that is uniformly distributed $[0,1]$, and $\Delta W_j^0(i)(j = 1,2,\ldots.,M, i = 1,2,\ldots.,C)$ represents the range of independent movement of the $j-th$ elephant in the $i-th$ dimension at the starting time. Both $\Delta W^{min}(i) = -\Delta W^{max}(i)$ and $\Delta W^{max}(i) = E \times \left(W^{max}(i) - W^{min}(i)\right)$ represent the lower and upper bounds of the $i-th$ dimensional autonomous motion space. Generally speaking, E can be seen as 0.005 for improved outcomes,

$$YW_j^0(i) = W_j^0(i) + \Delta W_j^0(i) \quad (11)$$

As evolution advances, the autonomous range of mobility of each elephant should likewise diminish as individuals become closer to one another. Therefore, the independent moving range updates technique in equation (12) is used.

$$\Delta W_j^{it+1}(i) = \left[0.9 - \left(0.8 \times \frac{it}{it_{max}}\right)\right] \times \Delta W_j^{it}(i) \quad (12)$$

Enhancement of the family clan's renewal technique: The mother elephant was the best person in each family clan, and all other clan members learn from the generative image. While clan members are responsible for maintaining population diversity to provide the mother elephant with superior evolutionary information for quick convergence, the mother elephant was primarily responsible for swiftly investigating the area where the hypothesized optimal location was located.

(1) A method of updating each clan member individually based on the autonomous location traction equation (13), this section proposes a way to update the individual population members based on autonomous location traction to better maintain species variety and avoid significantly slowing down the algorithm's rate of convergence.

$$W_{FCj,n}^{it+1} = \begin{cases} ZX_{FCj,n}^{it+1}(i) + q \times \alpha \times \left[W_{FC_{NC-j,N}}^{it}(i) - W_{FCj,n}^{it}(i)\right] \\ \quad + q \times \alpha \times \left[W_{MC,Rm}^{it}(i) - W_{FCj,n}^{it}(i)\right], \ if\ n > \frac{Ne}{2} \\ ZM_{FCj,n}^{it+1}(i) + q \times \alpha \times \left[W_{FCj,N}^{it}(i) - W_{FCj,n}^{it}(i)\right] \\ \quad + q \times \alpha \times \\ \quad \left[W_{MC,Rm}^{it}(i) - W_{FCj,n}^{it}(i)\right], else \end{cases} \quad (13)$$

In the $Nc-j$ family group $W_{FCM_{d=j,}}$ at the $j-th$ iteration, the matriarch of the female elephant was represented by $W_{FCM_{d=j,N}}^{it}$. After sorting at $it+1$ iteration $ZX_{FCj,n}^{it+1}$ was the autonomous position of the $n\left(n = 1,2,\ldots.,M_f\right)$ clan member, and equation (14) shows that q was a uniformly spread range form $[0,1]$. α was the improved adaptable scaling factor.

$$\alpha = 2 - \left(d \times \frac{it}{it_{max}}\right) \quad (14)$$

Where d was a fixed value that was typically set to 0.5 to get the best results, while the optimization issue itself requires in different values.

(2) An autonomous location traction-based individual update method for matriarchs is employed; as previously stated, the globally optimal individuals swiftly approach the globally optimal region after traversing each of the matriarchs in the ECO algorithm. This section suggests an autonomous position, traction-based matriarch updating approach, as illustrated in equation (15).

$$W_{FCj,n}^{it+1}(i) = ZX_{FCj,n}^{it+1}(i) + q \times \beta \times \left[W_{Best}^{it}(i) - W_{FCj,N}^{it}(i)\right] \quad (15)$$

The scaling factor β was determined using equation (14), while $ZX_{FCj,N}^{it+1}$ was the independent movement location of the matriarch in this clan at the $it+1$ iteration, acquired similarly to equation (16).

$$\beta = 3 - \left(d \times \frac{it}{it_{max}}\right) \quad (16)$$

Improvement of the individual renewal method of the male elephant clan: According to the ECO algorithm, the male elephant clan was essential in creating globally ideal locations for female clan leaders and substituting certain family members to supply evolutionary data. Despite this, the number of male elephants might add to the diversity of the family clan. In light of this, equation (17) provides the male elephant individual renewal formula to guarantee that the male elephant clan has particular population diversity and generates as much evolutionary information as possible.

$$W_{MC,m}^{it+1}(i) = ZX_{MC,m}^{it+1}(i) + q \times o \times \left(W_{Center}^{it} - W_{MC,m}^{it}(i)\right) \quad (17)$$

In the $it+1$ iteration of the male elephant clan $ZX_{MC,m}^{it+1}$ represents the autonomous movement location of the $m-th\left(m = 1,2,\ldots,M_f\right)$ elephant. Equation (18) illustrates that the o was determined using W_{Center}^{it}, which was the location of the maternal elephant patriarch in each family clan in the $it-th$ iteration.

$$W_{Center}^{it} = \frac{1}{Nc-1} \times \sum_{j=1}^{Nc-1} W_{FCj,N}^{it} \quad (18)$$

Improvement of individual replacement strategy for part of the family clan: Enhance the plan for replacing adult elephants. The following adult elephant replacement was suggested to guarantee the algorithm's speed of convergence and boost the variety of the creative ad images, as adult elephants are not the superior elephants within this clan. Equation (19) indicates the central position of all clan members. Otherwise, as indicated by equation (20), the superior person was chosen to replace the real adult elephant from both the new individual and the original adult elephant.

$$W_{FCj,Gm}^{it+1} = \frac{1}{Ne}\sum_{j=1}^{Ne} W_{FCj}^{it+1}(i) \quad (19)$$

$$W_{FCj,Cal\ e}^{it+1}(i) = W_{FCj,Gm}^{it+1}(i) + q \times \left[\frac{W_{FCj,Rf}^{it+1}(i)+W_{MC,Rm}^{it+1}(i)}{2} - W_{FCj,Gm}^{j+1}(i)\right] \quad (20)$$

Improve the inferior small elephant replacement strategy: The ECO algorithm replaces the poor individuals in family clans to maintain population diversity, but reduces convergence speed. Early iterations have significant differences, while late iterations focus on population diversity. The worst 0.3Ne tiny elephants in each family clan are replaced with new individuals in the evolutionary stage. Equation (21) generates new individuals during the pre-evolutionary period, where $it < itmax$. The $it+1$ iteration of the family clan W_{FCj}^{it+1}, where $W_{FCj,x}^{it+1}(i)$ was the worst one to be replaced.

$$W_{FCj,Cal\ e}^{it+1}(i) = W_{FCj,x}^{it+1}(i) + q \times \left[\frac{W_{FCj,Rf}^{it+1}(i)+W_{MC,Rm}^{it+1}(i)}{2} - W_{FCj,x}^{it+1}(i)\right] \quad (21)$$

AECO enhances SC-StyleGAN by tuning hyperparameters using elephant-inspired population dynamics. Each elephant's position represents a candidate solution, evolving through clan-based exploration and adaptive updates. This improves convergence and avoids common GAN issues. However, the mapping between AECO's search positions and StyleGAN's exact hyperparameters (like learning rate or noise scale) should be clarified.

4 Results and discussion

All experiments used Python 3.10.1 on an NVIDIA Tesla V100 GPU. AECO-SC StyleGAN trained for 50 epochs (1,000 iterations each) in approximately 12 GPU hours, outperforming Adam (15 GPU hours) in efficiency. The proposed strategy was assessed and its effectiveness was determined using the following indicators: Normalized Discounted Cumulative Gain (NDCG), accuracy, and weighted F1, The Fréchet Inception Distance (FID), Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR). Although AECO-SC StyleGAN is a generative framework, its output creatives are evaluated using a downstream binary classification task predicting ad engagement (high vs. low CTR). All models, including baselines like VGG + Layout + NIMA and XCEPTION, are evaluated on this task for a fair comparison, also implementing the baseline method to this research. Table 3 represents hyperparameters for AECO-SC StyleGAN-based framework used in dynamic advertising creative optimization.

Table 3: Hyperparameter Settings for AECO-SC StyleGAN Framework

Hyperparameter	**Value**
Batch Size	32
Learning Rate (Generator)	0.0001
Learning Rate (Discriminator)	0.0004
Epochs	200
Image Size	256 × 256 × 3
Latent Vector Dimension (z)	512
Dropout Rate	0.3
Activation Function	Leaky ReLU (α=0.2)
Normalization	Instance Normalization
AECO Population Size	30
AECO Max Iterations	100

4.1 Evaluation task

The primary task is a binary classification of ad creatives into 'high engagement' vs. 'low engagement' based on historical CTR data. Ads with CTR above the 75th percentile were labeled as high engagement (1), and others as low engagement (0). This classification target enables the model to learn aesthetic and contextual cues that align with user interaction patterns. The dataset was split 70/15/15 for training, validation, and testing. Evaluation was conducted on the unseen 15% test set. Performance metrics included NDCG, classification accuracy, and weighted F1-score FID, SSIM, and PSNR. Baseline

models included Visual Geometry Group Layout feature Neural Image Assessment (VGG + Layout features + NIMA) [20], XCEPTION [21], AdvAE-GAN [22] , BicycleGAN [22], V-GAN [23], and Vanilla GAN [23]. All models were trained under similar hardware and optimization conditions to ensure a fair comparison. Table 4 shows the comparison of classifiers and their performance evaluation results.

The evaluation pipeline begins with AECO-SC StyleGAN generating advertising creatives. These outputs are labeled based on a CTR threshold to indicate high or low engagement. A classifier then predicts engagement levels, allowing metrics like NDCG, Accuracy, and Weighted F1-score to assess how well the generated creatives align with user interaction patterns.

4.2 Accuracy and loss

The training accuracy and loss over 50 epochs for the proposed AECO-SC StyleGAN, XCEPTION, and VGG + Layout + NIMA are displayed in Figure 5(a, b). The AECO-SC StyleGAN consistently achieves superior accuracy and inferior loss, demonstrating better learning efficiency, faster convergence, and more stable training. Accuracy values were mentioned in percentage. Both training and validation accuracy curves show steady growth and eventual stabilization, indicating effective learning with minimal overfitting. Similarly, the loss curves for training and validation exhibit a clear downward trend, reflecting successful convergence. These results highlight the model's ability to efficiently capture cross-platform advertising dynamics, generate high-quality creatives, and maintain strong generalization across datasets, ultimately improving engagement prediction performance.

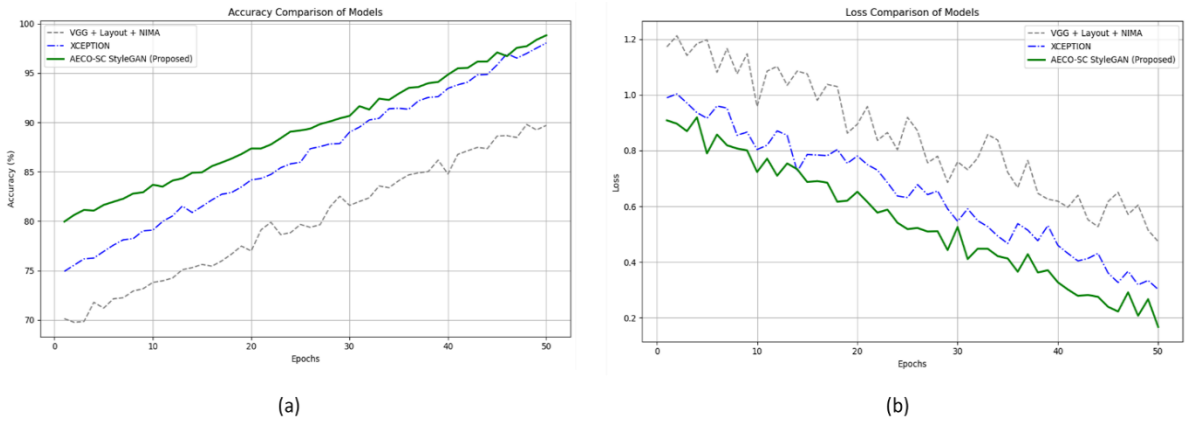

Figure 5: Accuracy and Loss Comparison of Models

4.3 Ad image dimension distribution

The GAN ad image dimension distribution operates as a cross-platform deep learning framework that generates multiple platform-optimized sizes for presented images. Standard display and mobile ad dimensions are the format choices for most images, which guarantee visual performance while ensuring cross-platform compatibility. Figure 6 displays the Ad image dimensions across digital platforms.

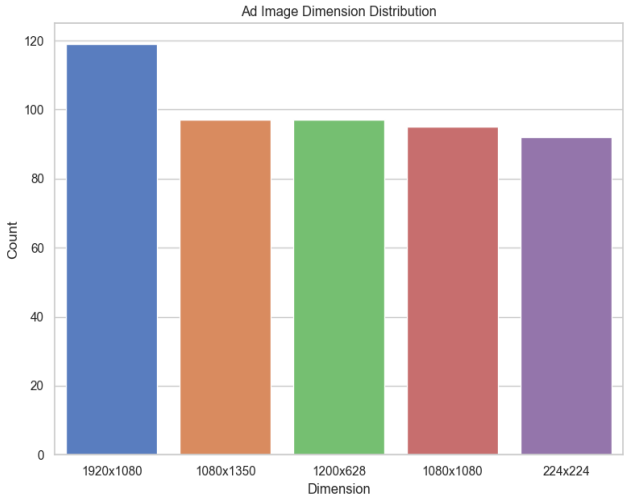

Figure 6: Ad image dimensions across digital platforms

4.4 Clicks-through rate (CTR) by platform

The CTR performance stands tested across different platforms through the use of a GAN framework for dynamic ad optimization. Results indicate that performance metrics vary between platforms since mobile achieves better CTR than desktop. Through its creative adaptation, the GAN model demonstrates high engagement while showing the power of deep learning as a means to improve cross-platform digital advertisement results. Figure 7 shows the CTR distribution across four social platforms.

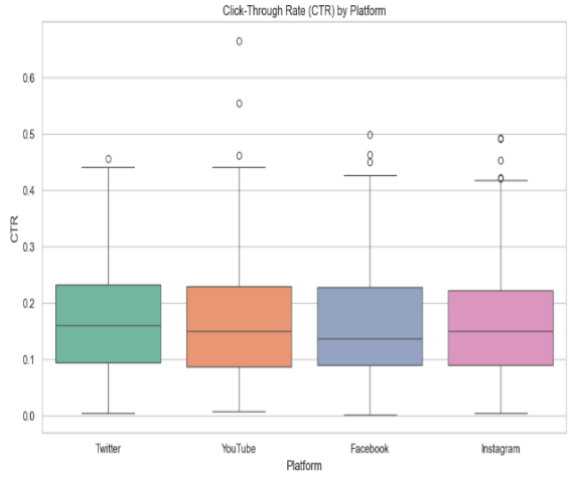

Figure 7: CTR distribution across four social platforms

4.5 Convergence and runtime analysis

To compare the stability of the training between AECO and Adam, by run both for 100 iterations shown in Figure 8. AECO demonstrated a quicker and smoother convergence, as seen by its early near-zero loss. Ad creative generation requires a stable and fast system, as it works with many constraints in quick optimization. By using adaptive learning, AECO avoids the problems of local minima and maintains consistency, which makes it effective than Adam and RMSprop for cross-platform advertising.

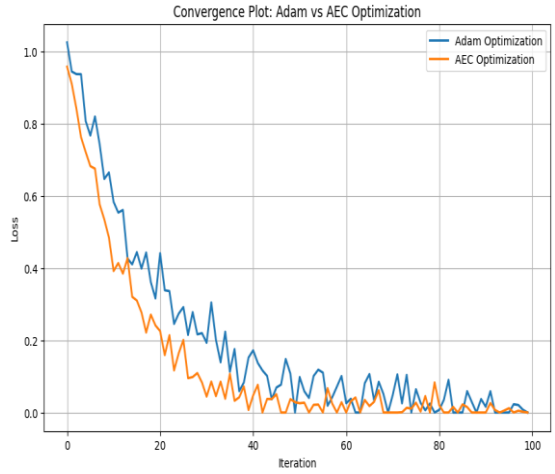

Figure 8: Outcomes of convergence and runtime analysis

4.6 NDCG

The NDCG score was applied to measure how relevant and well-arranged the ad creatives were for users. Because of this, NDCG is better suited for this task, as it rewards higher positions for predicting relevant content. A better NDCG means the model ranks the most engaging and appropriate content first, which helps in dynamic advertising situations where space and time are both limited. The NDCG for the AECO-SC StyleGAN was 0.61, much better than the NDCG of 0.22 for the baseline VGG + Layout + NIMA model. From this, we can see that our model helps us better find and rank the strongest ad creatives first. With this accuracy, marketers are better equipped to promote content that has a significant effect. Figure 9 illustrates the NDCG scores of all the evaluated models.

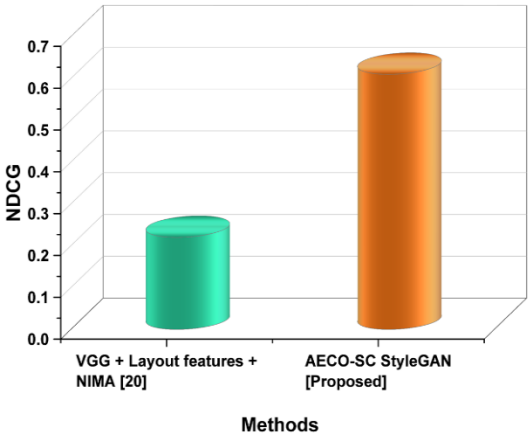

Figure 9: Illustrates NDCG performance results

4.7 Accuracy

Accuracy indicates how effectively the classifier predicts whether generated advertisements will result in high or low user engagement (based on CTR), thus assessing the effectiveness of the generated creatives. The high accuracy in generating platform-specific ad creatives consistently aligns with user engagement metrics, outperforming baseline models in aesthetic coherence, contextual relevance, and predictive performance across platforms. The results demonstrate that XCEPTION achieved an accuracy of 98.27%, while AECO-SC StyleGAN performed slightly better with an accuracy of 98.48%, showcasing their effectiveness in the given task.

4.8 Weighted F1

The F1-score balances precision and recall, crucial for imbalanced engagement data, indicating how well the model generates relevant, high-performing ads while minimizing misclassification. The Weighted F1 score was a metric used to evaluate the performance of a GAN in dynamic advertising creative optimization, emphasizing precision and recall across various platforms. Table 4 gives Evaluation of Ad Engagement Prediction Based on Generated Ad Creatives. The results show that AECO-SC StyleGAN outperforms XCEPTION, achieving a higher Weighted F1 score of 98.5% compared to 98.2%, demonstrating superior performance in dynamic advertising creative optimization. Figure 10 displays the accuracy and weighted F1 evaluation results.

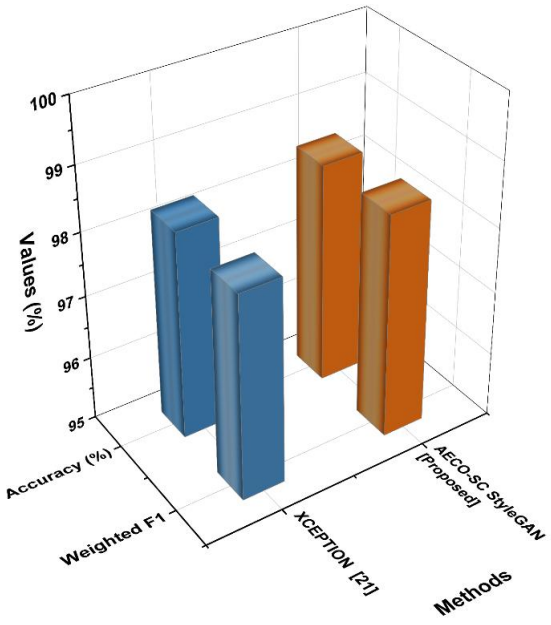

Figure 10: Accuracy and Weighted F1 Evaluation Results

Table 4: Evaluation of ad engagement prediction based on generated Ad Creatives

Method	NDCG	Accuracy (%)	Weighted F1 (%)
VGG + Layout features + NIMA [20]	0.22	-	-
XCEPTION [21]	-	98.27 %	98.2 %
AECO-SC StyleGAN [Proposed]	0.61	98.48 %	98.5 %

4.8 Statistical evaluation of model performance

To address this, we have conducted additional experiments using five different random seeds. For each seed, the model was trained and evaluated independently using the same data split. We now report the mean ± standard deviations for the key evaluation metrics, including Normalized Discounted Cumulative Gain (NDCG), Accuracy, and Weighted F1-score. Performance Comparison of Creative Generation Models on the Ad ImageNet Dataset given below Table 5.

Table 5: Performance comparison of creative generation models on the Ad ImageNet dataset

Method	NDCG (Mean ± SD)	Accuracy (%) (Mean ± SD)	Weighted F1 (%) (Mean ± SD)
VGG + Layout + NIMA [20]	0.22 ± 0.015	94.62 ± 0.40	94.3 ± 0.38
XCEPTION [21]	0.45 ± 0.020	98.27 ± 0.25	98.2 ± 0.21
AECO-SC StyleGAN [Proposed]	0.61 ± 0.018	98.48 ± 0.22	98.5 ± 0.19

In addition to reporting the mean ± SD, we performed paired t-tests to evaluate whether the improvements over baseline models are statistically significant. The results confirm that the performance gains of AECO-SC StyleGAN over XCEPTION and VGG+NIMA are statistically significant with $p < 0.01$ for all three metrics.

4.9 Performance comparison of generative models

FID scores of the suggested AECO-SC StyleGAN are contrasted with those of other GAN-based baselines in Figure 11. Among the tested methods, the proposed AECO-SC StyleGAN delivered the best quality, with an FID score of 38.4752, compared to 42.3256 for AdvAE-GAN [22] and 45.0208 for BicycleGAN [22].

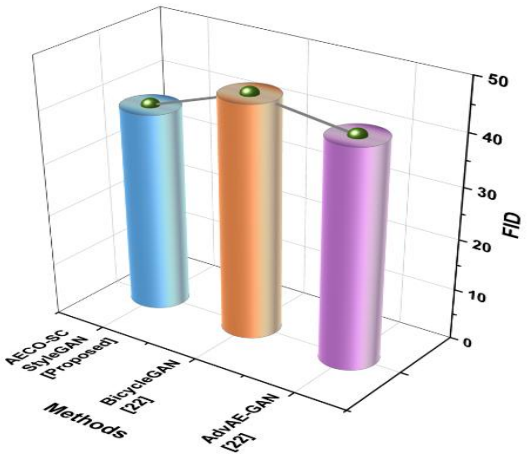

Figure 11: Generative quality evaluation model comparison results.

The SSIM and PSNR metrics for AECO-SC StyleGAN and other GAN variations are shown in Figure 12. Higher PSNR and SSIM values indicate better image fidelity and structural similarity to the original images. The AECO-SC StyleGAN shows the highest PSNR of 35.8 dB and an SSIM of 0.95 which is better than the PSNR of 33.5 dB and SSIM of 0.92 for V-GAN [23] and the PSNR of 28.4 dB and SSIM of 0.85 for Vanilla GAN [23]. It means that AECO-SC StyleGAN is able to create images that are more clearly detailed and accurate than other styles.

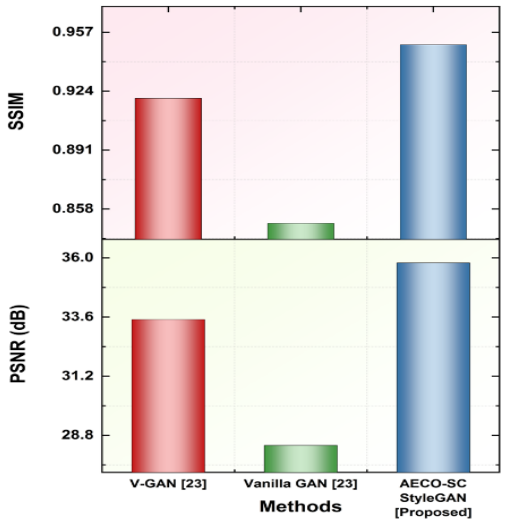

Figure 12: Model comparison results of image quality assessment.

4.10 Visual results and assessment of visual fidelity

To evaluate the visual fidelity of the proposed AECO-SC StyleGAN, we generated advertisement creatives using the Ad ImageNet dataset. Figure 13 illustrates side-by-side examples of generated ads, showcasing a variety of product categories including fashion, electronics, and skincare. The generated ads closely match real ones in layout, color schemes, and promotional text, reflecting platform-specific design aesthetics. While maintaining coherence, the model introduces subtle variations that add diversity and creativity. These results demonstrate that AECO-SC StyleGAN effectively replicates real ad characteristics, providing a scalable and automated approach for cross-platform ad generation.

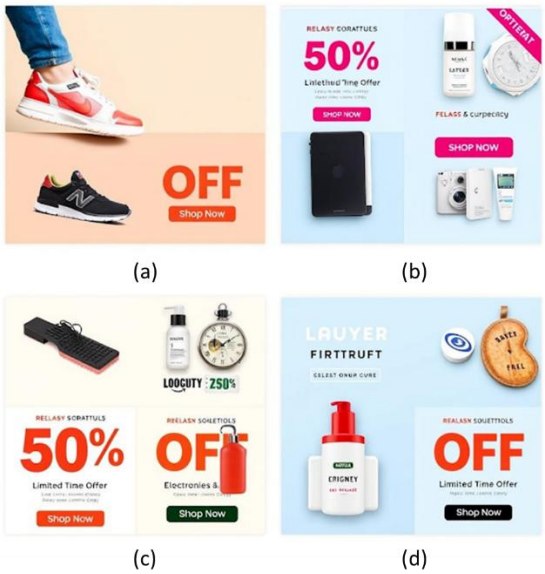

Figure 13: Generated Ad Creative using AECO-SC StyleGAN

4.11 Discussion

Dynamic advertising creative optimization across multiple platforms aims to enhance user engagement and conversions by generating context-aware, personalized ad content. Traditional models such as VGG combined with Layout features and NIMA [20] rely on fixed image features, limiting their capacity to capture the full spectrum of complex, interactive visual and contextual patterns inherent in cross-platform environments. As a result, the creatives they generate often lack adaptability and personalization, making them less effective in varied user scenarios. Meanwhile, XCEPTION-based GAN [21] models, although capable of deeper feature extraction, are hindered by their high computational and memory demands. Their complex operations limit scalability and pose challenges for deployment on lightweight or real-time advertising platforms, reducing practicality in widespread commercial use.

In contrast, the proposed AECO-SC StyleGAN framework addresses these limitations by integrating adaptive hyperparameter tuning and spatial conditioning to generate high-fidelity, semantically consistent creatives tailored to specific platform requirements. AECO enhances convergence and training efficiency, while SC-StyleGAN ensures visual and contextual alignment across formats. This leads to better performance and improved resource utilization, offering a scalable and intelligent solution for dynamic advertising creative generation in diverse deployment environments.

While AECO-SC StyleGAN improves convergence speed and reduces memory consumption relative to baseline GANs during training, it still requires substantial computational resources overall, particularly due to its large model size and high-resolution output generation. However, once trained, the model supports relatively efficient inference, making it suitable for real-time or near-real-time deployment scenarios.

5 Conclusions

The DL framework uses GAN for dynamic advertising creative optimization, enabling effective cross-platform strategies to enhance ad personalization and performance in real time. Data collection involved the Ad ImageNet dataset, consisting of multimodal ad samples. Preprocessing included image resizing, tokenization, and intensity normalization. This approach demonstrates a scalable, efficient method for cross-platform ad creative optimization, ensuring higher engagement and visual coherence. The results show that the AECO-SC StyleGAN method achieved an NDCG of 0.61, an accuracy of 98.48%, and a weighted F1 score of 98.5%. These metrics highlight the method's high performance in optimizing dynamic advertising creatives with excellent precision and relevance. Although AECO-SC StyleGAN shows promising results in generating optimized ad creatives with high quality, the training process remains computationally intensive due to the high-resolution outputs and multiple conditioning layers. The model may face challenges in ensuring consistency across diverse platforms, handling large-scale real-time data, and optimizing for varying audience preferences. It also requires significant computational resources for training. Future scope could focus on improving real-time adaptability, cross-platform integration, and reducing computational costs for broader adoption in dynamic advertising.

5.1 Limitations and future work

While AECO-SC StyleGAN shows promising results, it presents notable limitations. First, training the model requires significant computational resources, with 30+ hours of training time on high-memory GPUs, limiting accessibility for smaller teams. Second, generalization across domains remains a challenge. Early tests on ad categories like automotive and electronics suggest reduced performance, warranting domain-adaptive retraining. Third, although AECO-SC generates high-quality creatives, its deployment in real-time ad systems is untested. Future work will explore integration with ad delivery platforms and A/B testing frameworks to assess live performance metrics such as CTR and Return on Ad Spend (ROAS), moving toward a fully automated ad generation and evaluation pipeline. Focus on model compression and distillation techniques to reduce training time and memory consumption without sacrificing output quality.

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Adaptive Control of PV-Integrated Power Grids Using KNN-Smote-GCN And Mpc Techniques

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Keywords: auxiliary control technology, artificial intelligence, KNN-SMOTE-GCN model, large power grid, MPPT control

Received: May 29, 2025

As the global energy crisis intensifies, the integration of renewable energy—particularly photovoltaic (PV) systems—has become vital for achieving a sustainable and resilient power infrastructure. This study focuses on dynamic modeling and efficient control of grid-connected PV systems to enhance power quality and system reliability. An adaptive PI controller is employed for voltage regulation, with a maximum power point tracking (MPPT) method ensuring optimal energy harvesting. A DC-DC boost converter and a three-phase PWM inverter are incorporated, with MATLAB used for simulation. The proposed approach integrates Model Predictive Control (MPC) with Graph Convolutional Networks (GCN) to manage grid instability and improve energy efficiency. A novel KNN-SMOTE-GCN algorithm is developed to mitigate voltage distortion, harmonic currents, and power fluctuations. The system replicates the behavior of traditional generators under disturbances, promoting renewable integration without compromising stability. Key performance metrics such as voltage deviation, reactive power fluctuation, power loss, and total harmonic distortion (THD) are analyzed.

Povzetek: Integrirani KNN-SMOTE-GCN in MPC izboljšata stabilnost PV-omrežij z natančnim MPPT, učinkovitim nadzorom napetosti ter zmanjšanjem izgub, nihanja jalove moči in THD. Metoda poveča kakovost energije in zanesljivost šibkih omrežij z visoko penetracijo PV.

1 Introduction

The reckless use of hydrocarbons and nuclear power threatens environmental safety and causes significant pollution. The truth of this energy source is prompting a global movement toward renewable energy sources that are less harmful to the environment, including as wind power, PV, and others. Distributed power generating systems that employ renewable energy sources have garnered significant interest due to the current focus on clean power generation [1], [2], [3]. Recent advances in photovoltaic technology have led to the rapid adoption of renewable energy production based on solar PV by both commercial and residential sectors. Reduced main power system load, maximum savings, and reactive power support are just a few of the benefits that the distribution grid may reap from integrating distributed solar PV generating plants [4], [5]. electricity quality and dependability are both enhanced by solar PV electricity, which lessens the strain on the central grid. The energy quality usually drops as the use of non-linear loads increases. It is also well known that most non-linear loads that produce more complex harmonics and demand reactive power are electronic power equipment. This action causes voltage distortion, which impacts all subsequent loads linked to the identical PCC. Optimal performance of solar photovoltaic inverters is hindered by the unpredictability of sun irradiation [6], [7]. Two examples of supplementary services that the inverter's extra capacity may offer are reducing source current harmonics while adjusting reactive load power. When it comes to PV-integrated systems, MPPT is a go-to for reducing harmonics. One method for reducing PV system grid current harmonics is the adaptive P&O (perturb and observation) MPPT algorithm, which incorporates sliding mode control [8], [9]. The goal of auxiliary regulation is to maintain grid stability by modifying power system characteristics in response to imbalances, fluctuations, and disruptions. The grid, however, functions within reasonable bounds and adapts efficiently to shifts in both generation and demand [10], [11]. Controlling the grid frequency entails modifying either electricity production or consumption to keep it within predetermined boundaries. Ensures that electrical equipment continue to

function correctly by keeping voltage levels within certain limits. Optimizes system performance by balancing the production and consumption of both reactive and active electricity. More conventional approaches, such as DL, Machine Learning, etc [12]. These systems are often studied for their possible use in power system optimization, control performance, and forecasting. Due to a lack of sophisticated automation infrastructure, many system operations are being performed with modest degrees of automation at the time. AI is expected to play a significant role in the future power system, according to several studies, technical papers, and case studies [13], [14]. This is because AI will introduce state-of-the-art techniques of system optimization while simultaneously decreasing the need for human participation. Research on AI for grid system power flow optimization is now at a premium. The auxiliary services that help to reduce frequency variations are crucial to the reliability of ac power networks. Large synchronous generators' electromechanical inertia is the only available resource for absorbing frequencies disturbances on subsecond time scales at the moment. This means that switching from traditional thermal power plants to NREs, which are inertialess, puts grid stability at risk from things like unexpected power production outages. Grids with high penetrations of NREs may suffer from electromechanical inertia, which may disrupt system stability. To address this, virtual synchronous generators have been suggested, which mimic traditional generators. In this paper, we provide a new method of controlling virtual synchronous generators that uses a configurable time scale to reduce the supplied inertia, which is large at short intervals to absorb faults as effectively as traditional generators but sets in motion coherent frequency oscillations when it doesn't [15], [16]. We test how well our adaptive-inertia approach handles large-scale transmission networks that experience unexpected power outages. It is more stable than earlier proposed methods and consistently outperforms traditional electromechanical inertia. The numerical simulations demonstrate that the quasioptimal placement of adaptive-inertia devices enhances the damping of interarea oscillations and effectively absorbs local faults. In future low-inertia power grids that have significant penetrations of NREs, our findings demonstrate that the suggested adaptive-inertia control system is a great way to improve grid stability [17], [18], [19], [20].

1.1 Problem statement

In today's world, contemporary power systems are complemented with large-scale renewable energy systems, allowing for more efficient operations. Accurate energy production and efficient control systems to manage while guarantee a reliable power supply are also necessary for optimum power systems. However, there is a degree of uncertainty due to the high electrical consumption and the sporadic balance of supply. Also, traditional power sources aren't practical for such a difficult job, and they drive up energy prices.

The next step was to improve electrical distribution networks' power quality by using an optimization approach. It employs a hybrid design that incorporates shunt and series compensators to address voltage drops, harmonics, and imbalance, among other power quality concerns. Afterwards, MPPT was used to derive the greatest amount of power from the grid system. Controller for MPC to ascertain the system's overall stability and performance. In addition, the model was tested on the MATLAB platform and its reliability was assessed by measuring voltage variation, reactive power fluctuations, grid current, and THD.

1.2 Motivation

Many issues, including power quality, stability, dependability, and supply management, may arise as a result of the increasing need for big power grid-connected systems. In addition, the total system performance might be negatively impacted by power quality concerns as a result of variations. It is possible for there to be an imbalance in the power demand and generation frequency fluctuations. Next, problems with the power factor, such as a low power factor, might cause the power distribution system to lose more power and increase energy usage. Voltage instability is the root cause of both linear and non-linear problems. Voltage regulation may be subpar due to the persistent use of insufficient control mechanisms in power grid systems. Ensuring the stability and operation of big power networks also relies heavily on rules and norms that specify acceptable power quality values. As a result, grid systems need an intelligent auxiliary regulatory technology that can effectively lessen the burdens on them.

1.3 Contributions

Despite the paper's focus on intelligent real-time power grid regulation and control, no mention of research into building the comprehensive functional foundation of a dispatching intelligent assistant driving network is made. The study and evaluation of real-time regulation and control business aims to explore fresh artificial intelligence application methods for various business processes, as well as the principle and implementation characteristics of a grid-assisted control system based on AI thinking and decision-making in regulation and control operations. In order to achieve the shift from empirical to intelligent control and enhance the degree of control over the power grid, we provide solutions to raise the bar for artificial intelligence in terms of both interaction and performance. In order to achieve maximum power generation, it is necessary to control the working point of photovoltaic panels. For this regulation procedure to be successful,

there are two primary components that are required: an MPPT algorithm that serves as the reference for the MPP, and a voltage controller that guarantees a steady functioning at the MPP.

One of the most significant benefits of adopting MPC is that it has the ability to simplify the process of developing a variety of controllers while also working to accommodate system limits within its formulation. In addition, the introduction of KNN-SMOTE-GCN as a user-friendly optimization approach is suggested in this study as a means of enhancing the cost function of the MPC controller.

This research work is structured as follows: Section 2 describes the research articles that were relevant to the framework that was developed; Section 3 describes the problem statements; Section 4 explains the proposed hybrid framework; Section 5 analyzes the results of the methodology that was proposed; and Section 6 describes the research conclusion.

2 Related work

Experts from [21] grid operators use neuro-fuzzy logic for dynamic reactive power adjustment. The energy storage system may also be effectively managed using that logic. After that, SP UPQC was used to improve the electrical distribution networks' power quality. It employs a hybrid design that incorporates shunt and series compensators to address voltage drops, harmonics, and imbalance, among other power quality concerns. Afterwards, maximum power point tracking was used to derive the greatest amount of power from the electricity network. Controller for Model Predictive Control to ascertain the system's overall stability and performance. In addition, the model was tested on the MATLAB platform and its reliability was assessed by measuring voltage variation, grid current, reactive power fluctuations, and Total Harmonic Distortion.

Enhancing the effectiveness of section control of large power grid, altering the traditional experience-led dispatching mode, and improving the intrinsic safety level of the power grid are all goals of the experimental team in [22]. They study intelligent section auxiliary decision-making algorithms in depth and build a new intelligent dispatching structure framework of the power grid using deep learning and simulation environments. To build a more realistic simulation of the power grid's dynamic characteristics under varied operating circumstances, an environment that is suited for the upcoming AC-DC hybrid big power grid is first built. Secondly, a scheduling agent that takes into account the power grid's characteristics and the dispatcher's behavior is researched using the power grid's historical operation data and the dispatcher's real control data. Finally, to address the issues of poor regulation speed, complex regulation decision-making, and inadequate technical support ability, authors study the technology that generates and verifies strategies for multi-dimensional scheduling agents using deep reinforcement learning. In addition to providing solid technical support for power grid operation, that research may enhance the accuracy and effectiveness of section dispatching decision-making, optimize the section control strategy continually, and more.

According to [23], when a problem occurs, the generator network determines the unit output plan using the combined wind, light, and electrical demand data from a northwest area of China. A specialized system generation fault recovery strategy is developed for that grid fault using data on actual power load while actual renewable energy output before and after the fault. The strategy aims to minimize the cost of system power generation while considering the constraints of secure operation of the system. It turns out that the expert system's fault recovery method is much different from the one used in the early stages of training, and that the error value is very high. After a generative adversarial network is fully trained, it can approach the fault recovery expert system with an auxiliary decision-making scheme that works in different situations with different loads and new energy outputs, and it can keep the error between the two schemes to less than 5%. Results from studies examining power grid fault recovery strategies using models of generative adversarial imitation learning networks demonstrate the force control system's capacity for autonomous and secure fault recovery.

With the goal of conducting real-time tracking on the operating state of the power grid, eliminating potential safety hazards, and upgrading the power grid from "manual analysis" scheduling to "intelligent analysis" scheduling, the authors of [24] propose an integrated framework to aid decision-making of online accident processing using large power grids. The study covers five aspects: integrated information support system, aid decision-making afterwards, risk perception in grow, online fault diagnosis, and visual display.

The writers of the cited work, [25] an online trend analysis technology with a functioning mode arrangement for large power grids is suggested, drawing on references to the growth of intelligent dispatching support systems and their dynamic security assessment technologies, in light of the growing importance of grid dispatching operations in understanding future state security changes. Estimated power flow in the future is based on the power grid's present operating mode, online stability conclusion, data from fresh energy and load forecasts, dispatch scheduling, and dispatch operation adjustment. The auxiliary decision-making approach for control allows for fast assessment of future security situations and trends. With the use of that technology, the power grids of Heilongjiang and Central China have been able to transition from empirical to intelligent control, and precontrol techniques for

complicated power grid dispatching operations have received technological support.

The tiny sensor sample unit, energy metering device, communication unit, protection control device, performance evaluation unit, etc. were all combined by the experimenters of [26]. In conjunction with the transformer, keeping its original dimensions and construction. It is possible to analyze the measured data locally, allowing for an intelligent and transparent observation of the performance indicators of the transformer. Simultaneously, it can accomplish intelligent monitoring, reduce energy consumption and save energy, and aid in the creation of new power systems without uploading a mountain of normal and abnormal data.

Using deep reinforcement learning, the authors of [27] provides an auxiliary control method for large-scale power grid segments. An intelligent agent for power grid section control is built using the Deep Deterministic Policy Gradient algorithm. That agent provides real-time control methods in complex power grid settings, taking into account both the safety and economics of power grid operations. That justifies the proposal of a two-stage optimization approach that takes sensitivity into account. When operators are unable to remove the section restriction via real-time control, they offer them with the optimum market intervention strategy. At last, the efficacy of market intervention plans and real-time control mechanisms are tested via case studies. The methodology presented in that study improves the system's economy by lowering the clearing price through an average of 1.2% while the average adjustment amount through 37.6% under various section limits resulting from power generation components participating in the market, as compared to the current rules.

The authors of [28] looking at the power grid from a knowledge graph perspective, researchers were able to develop a functional framework for an intelligent evaluator that could assess static stability, make decisions based on that evaluation, and be an all-around smart algorithm. That evaluator took into account the stability state evaluation index while optimization control strategy data from various power grid operation scenarios. The implementation of a visual evaluation tool for large-scale power grid static stability was made possible with the introduction of technology for knowledge graph automation engines. To demonstrate the efficacy of the suggested approach, an example using a real-world electricity system is provided. Regulatory and control operators may benefit from the study's findings by better understanding the current state of operations and making more informed decisions about the power system. Explorationally, it may be useful for enhancing the building of online intelligent active security defense structures on big power grids.

3 PV generated system integrated to weak grid

The basic architecture of a three-phase grid-connected double-stage solar power plant is shown in Figure 1. The integration of solar electricity into the electrical grid is achieved via the employment of this sort of technology, which guarantees effective power conversion and maintains grid stability. To generate and transmit electricity from the solar PV array to the unreliable utility grid, the system relies on a number of moving parts, all of which contribute in different ways. The PV array generates the majority of the system's renewable electricity. It relies on a network of solar panels to generate DC power from sunlight. The PV array's power production is directly related to the amount of solar irradiation and temperature that it can operate at. Maximizing the conversion of solar energy into grid-ready alternating current electricity is the system's primary objective. To get the most power out of the solar PV system, the DC-DC boost converter is an absolute must. For maximum efficiency in power conversion, it raises the DC voltage produced by the PV array until it is equal to or greater than the DC-link voltage. In order to keep the PV array running at its optimum power point no matter what happens to the weather or irradiance, the boost converter works using a MPPT algorithm. An MPPT method known as Perturb along with Observe is used to optimize the amount of energy harvested by the PV array. One of the most popular ways to increase the output of solar PV systems is by using this algorithm.

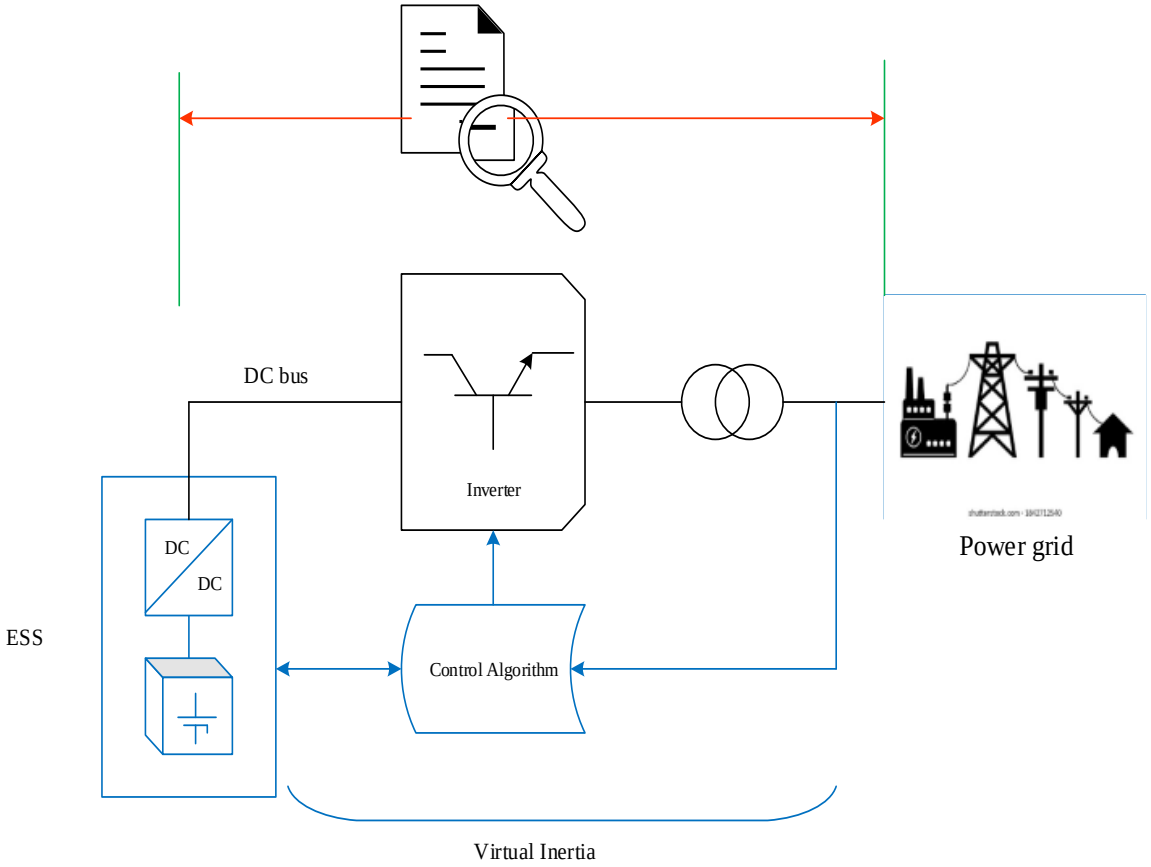

Figure 1: Auxiliary power control in large power grid

It works by monitoring the change in power output and making adjustments to the operating voltage of the PV array at regular intervals. When the power goes up, the adjustment stays the same; when it goes down, it goes in the other way. The technology is able to maintain optimal performance regardless of environmental changes because of this iterative procedure that continually monitors the PV array's MPP. By responding in real-time to variations in temperature and irradiance, the P&O MPPT algorithm keeps the boost converter operating at the ideal voltage input from the PV array. In areas where the amount of sunshine varies throughout the day, the efficiency of the solar PV system depends on this capability to monitor the MPP under changing circumstances.

3.1 PV array modelling

To enhance the voltage or current level, the PV panel uses numerous modules linked in series or parallel, accordingly. A current source, two types of resistance (series and shunt), with an antiparallel diode make up the equivalent circuit of a PV cell, as shown in Figure 2. The current source (I_s) is expressed by de following equation:

$$I_s = \left(\frac{G}{G_{ref}}\right)\left(I_{s\_ref} + K_{sc} \cdot \left(T - T_{ref}\right)\right) \quad (1)$$

where irradiance (G) and ambient temperature (T) are the two variables. The coefficient of short-circuiting current is denoted as K_{sc}. The following are the current, irradiation, as well as temperature under typical conditions: I_{s_ref}, G_{ref} and T_{ref}. The current changes with irradiation and temperature change, as shown in Eq. (1); yet, the I_{sat} fluctuation in temperature is the only determinant of current. In accordance with Kirchhoff's law, the PV panel's output current (v_{pv}) is given through:

$$I_{pv} = I_s - I_d - I_{shu} \quad (2)$$

Yes, it means we can:

$$I_{pv} = I_s - I_{sat}\left[exp\left(\frac{q\left(v_{pv}+(I_{pv}*R_{Ser})\right)}{nkT}\right) - 1\right] - \frac{V_{pv}+(I_{pv}*R_{Ser})}{R_{shu}} \quad (3)$$

With:

$$I_d = I_{sat}\left[exp\left(\frac{q\left(v_{pv}+(I_{pv}*R_{Ser})\right)}{nkT}\right) - 1\right] \quad (4)$$

And:

$$I_{shu} = \frac{V_{pv}+(I_{pv}*R_{Ser})}{R_{shu}} \quad (5)$$

3.2 DC-DC converter

Here is one way to express the transfer function of the boost converter:

$$v_m = \frac{1}{1-D} v_{pv} \quad (6)$$

The relationship between the average currents flowing into and out of an electrical device may be expressed as follows:

$$I_{pv} = \frac{1}{1-D} I_{dc} \quad (7)$$

The equation for the DC bus may be written as:

$$\frac{dv_{dc}}{dt} = \frac{1}{C}(I_{dc} - I_{inv}) \quad (8)$$

3.3 DC-AC inverter

It is possible to transform DC electricity into AC voltage with the frequency and amplitude of our choice thanks to the inverter, the adaptation step. The inverter control makes it possible to inject higher-quality currents and powers (P,Q) into the grid. The input/output inverter voltage relationship is defined as:

$$\begin{cases} v_{an} = (S_1 - S_2)v_{dc} \\ v_{bn} = (S_2 - S_3)v_{dc} \\ v_{cn} = (S_3 - S_1)v_{dc} \end{cases} \quad \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \frac{v_{dc}}{3} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix} \quad (9)$$

where v_{dc} is the DC voltage, $v_{in}(i = a, b, c)$ and $S_j(j = 1,2,3)$ consist of alternating current voltages and signals indicating the current state of the switches. Here is the equation for grid voltages:

$$\begin{bmatrix} v_{ga} \\ v_{gb} \\ v_{gc} \end{bmatrix} = \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} + R \begin{bmatrix} I_{ga} \\ I_{gb} \\ I_{gc} \end{bmatrix} + L \frac{d}{dt} \begin{bmatrix} I_{ga} \\ I_{gb} \\ I_{gc} \end{bmatrix} \quad (10)$$

The goal of studying and realizing the decoupling among the active (P) with reactive (Q) capabilities was to regulate them independently. If we want a fair system, we can just put down the powers P_g and Q_g as follows:

$$\begin{cases} P_g = \frac{3}{2}(v_{gd} I_{gd} + v_{gq} I_{gq}) \\ Q_g = \frac{3}{2}(\mathrm{v_{gq}I_{gd}} - \mathrm{v_{gd}I_{gq}}) \end{cases} \quad (11)$$

Indeed, we can write:

$$\begin{cases} \mathrm{P_g} = \frac{3}{2}\mathrm{v_{gd}I_{gd}} \\ \mathrm{Q_g} = -\frac{3}{2}\mathrm{v_{gd}I_{gq}} \end{cases} \quad (12)$$

where $\mathrm{v_{gdq}}$ as well as $\mathrm{I_{gdq}}$, which stands for grid current.

3.4 Normalization

The data were standardized to ensure that the model's accuracy was unaffected by dimensions. The min-max scaling approach was used for normalization in this research.

$$\hat{x} = \frac{x - min(x)}{max(x) - min(x)} \quad (13)$$

where $\hat{x}$ stands for the value of the normalized property. The function min(x) finds the lowest value in the values of the attributes while max(x) finds the highest value.

3.5 Missing value completion

One approach that uses nearby data points is KNN (K-Nearest Neighbors) interpolation. The goal of this technique is to estimate the target point's value by comparing it to the values of the K data points that are known to be the closest to it. For KNN interpolation, the fundamental procedures are these:

Choose the K-value: Choose the optimal K-size by determining its value, often using cross-validation.

Determine Distance: Find the total distance in geometric units between the current location and all other known locations. This is the formula for the distance in geometric units:

$$l(x_l, x_f) = \sqrt{\sum_{m=1}^{M} (x_{l,m} - x_{l,m})^2} \quad (14)$$

where x_i and x_j constitute data points, with M serving as the data dimension.

How to Determine the K-Nearest Neighbours: choose the K known points of data that are most closely located to the desired location.

Weighted averaging: Give each of your K neighbors a weight that is inversely proportionate to their distance from you. The formula for the weighted average interpolation for the K closest neighbors is

$$\hat{y} = \frac{\sum_{k=1}^{K} w_k y_k}{\sum_{k=1}^{K} w_k} \quad (15)$$

where y_k w_k is the weight that defines the distance from the location to be interpolated, and is often specified as the opposite proportion of the distance, and is the value of the k-th neighbour:

$$w_k = \frac{1}{d_k} \quad (16)$$

3.6 Deal with unbalanced data

In classification tasks, when minority samples are oversampled, an interpolation approach called Synthetic Minority Oversampling Technique (SMOTE) is used to address imbalanced datasets. By augmenting the dataset's diversity via the synthesis of fresh minority samples, SMOTE boosts the classifier's performance. The detailed procedures are these:

Pick a Representative Sample: Pick a representative sample at random from the minority group.

Determine the sample's k closest neighbors by using a distance measure.

Create a fresh sample by using the following formula to synthesize a neighbor from among these k neighbors at random:

$$\text{new\_sample} = x_1 + \lambda(x_1 - x_1) \quad (17)$$

3.7 Maximum power point tracking (MPPT)

The DC-DC boost converter controls the output of PV cells, which is one of its dual functions. As a result, MPPT is simplified and the output voltage is reliably controlled. This study combines a DC-to-DC converter with the widely known MPPT algorithm to optimize power extraction from PV panels. The operating point must be dynamically changed to the Maximum Power Point in order to accommodate changing weather conditions. The low cost and user-friendliness of the MPC algorithm led to its selection for MPPT. The MPC algorithm tracks the PV array's current and voltage down to the microsecond in order to foretell how a voltage modification will play out. This approach may be more resource intensive, but it can adapt to new conditions very fast. A little amount of energy can be saved in that gadget for use in seconds, and its performance is assessed by comparing the discharged and charged powers of the device. At all times, the following equation (4) describes how the charging and discharge rates of the constraints are combined with the battery efficiency.

$$W'_{ess}(n) = W'_{ess}(n-1) + \alpha_c p'_c \Delta n - \frac{1}{\alpha_d} p'_d \Delta n$$
$$\begin{cases} W'_{ess} \le W'_{ess}(n) \le W'_{ess} \cdot \max \\ p'_c(n) \le p'_{c\cdot max} \\ p'_d \le p'_{d\cdot max} \end{cases} \quad (18)$$

Where, W'_{ess} The energy storage limits are represented by p'_c, the charging power is p'_d, and the battery efficiency while charging and discharging is α_c.

3.8 Cost function

Using three crucial factors, including 1) the energy and discharging rate of each grid system, 2) the degradation cost of the battery and the discharge rate, and 3) the operation cost of other activities such service chargers and cable wear, we need to build the net cost function of the j^"th" grid system. First, use the following equation (5) to express the grid system discharge rate.

$$U_j\left[C'_j(n)\right] = p'(n)C'_j(n) \quad (19)$$

where $p'(n)$ represents the unit pricing with the grid aggregator at time n, and $c'_j(n$ stands for the discharge rate of each network grid at that specific time n. In this case, the degree of the generated aggregator grid system is shown by the increased energy wasted at the grid system. As a result, the grid power plant facilitates degradation cost in order to fulfill the particular demand at the grid system's discharge point. Equation (6) also allows for the modeling of the deterioration cost using a quadratic function.

$$d'_j\left[c'_j(n)\right] = \delta_j c'_j(n)^2 + \mu_j c'_j(n) + \lambda_i \quad (20)$$

Where, δ_j, μ_j and λ_i represents the degradation cost function and is represented by operational cost parameters $d'_j \mid c'_j(n)\big]$. Because of the limited integration between the operating cost parameters and the grid system's discharging rate, the constant value here must be associated with the grid system's discharge rate. However, using eqn. (21) in the following context, the cost function's simplicity is related:

$$f'_j[c'(n), p'(n)] = d'_j[c'(n)] + o'_j - U_j \mid C'_j(n)\big] \quad (21)$$

Where, o'_j is the formula for the lumped cost. Here, power is supplied by the grid at a net cost rate according to the electricity pricing unit with either an off-peak or peak-time tariff. Not to mention that the fixed price unit diverges from the original cost function.

3.9 Design of MPC

An extensive evaluation of the reference grid currents is carried out, taking into consideration various factors such as the presence of nonlinear loads at the Point of Common Coupling, regulation of the DC link voltage, and dynamic variations in PV power. This reference current is fed into the MPC controller, which then calculates the quantity of switching pulses required for optimum functioning. Considering the dynamic changes in PV power, ensuring stable control of the DC link voltage, while tolerating nonlinear loads at the PCC allow the system to efficiently supply reference grid currents that sustain efficient operation. The MPC controller enhances the system's general efficiency and stability by using these currents to identify the optimum switching pulses. As a result, the following equations (8), (9), (10), (11), define the key function of the charging station's net cost function in regards to multi-objective optimization problems.

$$\begin{aligned} &\min C_j(n) = \textstyle\sum_{j\in T(n)} s_j \mid C_j(n) + G(n)\big] \\ &C_j(n) = C_j(n) \forall j \ne i \in T(n) \\ &C^j_{min} \le C_j(n) \le C^j_{min} \forall j \in T(n) \\ &SOC^j_{min} \le SOC_j(n) \le 100\% \forall j \in T(n) \end{aligned} \quad (22)$$

Where, $C_j(n)$ represents the cost function of a grid system charging station, and is depicted as the minimization of the net cost function for every grid system charging stations,

$\sum_{j\in T(n)}$ appears as the energy cost function for the jth user over the time interval t. Additionally, the suggested KNN-SMOTE-GCN model's flowchart is shown in figure 2.

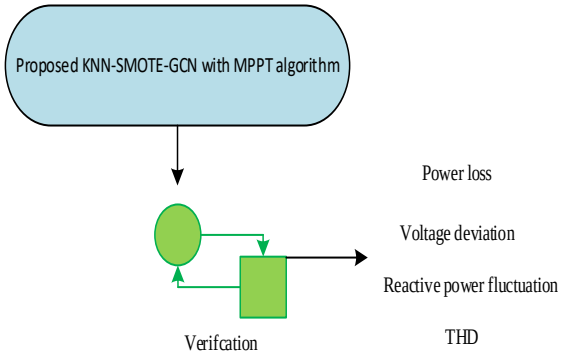

Figure 3: Typical Model Diagram for KNN-SMOTE-GCN

3.10 Graph convolutional network (GCN)

Building the association graph: A collection of nodes V and edges E may be characterized as a graph G(V, E). The connection between individual nodes v_f and v_f is signified by an edge $e_{fg} \in E$. In order to make it easier to aggregate information in the graph framework, an adjacency matrix A is built $A[i,j] = 1$ if the edge e_{fj} exists, besides $A[i,j] =$ **0** then.

The convolution theorem states that, in terms of forward propagation of the GCN, the Fourier transform of a convolution between two signals is the same as the pointwise multiplication of their individual Fourier transforms. Let $f * x$ Introduce the spatial domain convolution operation, which $x = \{x_1, x_2, \dots, x_n\} \in R^n$ stands for a dataset that has n pieces of data and $f = \{f_1, f_2, \dots, f_n\}$ are the neural network's trainable parameters. Using the Fourier transform, this procedure may be converted to the frequency domain.

$$F(f * x) = F(f) \cdot F(x) \tag{23}$$

Where the Fourier transform is denoted by F. Equation (1) may be simplified to describe the convolution process f*x in the spatial domain through the use the inverse Fourier transform F^{-1} to both sides.

$$\begin{aligned} f * x &= F^{-1}(F(f) \odot F(x)) \\ &= U\big((U^T f) \odot (U^T x)\big) \end{aligned} \tag{24}$$

Where U stands for the Fourier basis while $\odot$ means multiplication element-wise. The goal of the GCN was to provide a way for neural networks to use the association graph. The GCN does this by obtaining the Fourier basis from the graph's Laplacian matrix. What if $L_m = D - A$ is a graph's Laplacian matrix. One way to standardize it is as $L_m = I_N - D^{1/2}AD^{1/2} \in \mathbb{R}^{N\times N}$, where I_N is the neighboring matrix and denotes a unit matrix. For the degree matrix, D stands for $D_u \in \sum$, A_{uf}. Then, using the eigenvalue decomposition, one may derive the Fourier basis, U, and the eigenvalue matrix ∧.

$$U_\wedge U^T = L_m, \lambda = diag([\lambda_0, \dots, \lambda_{N-1}]) \tag{25}$$

U is a set of orthogonal matrices satisfying the Fourier transform's mathematical constraints, based on the Laplacian matrix's properties. The diagonal matrix, denoted as $g_e = diag(U^T f)$. Next, we may simplify Equation (2) by following these steps:

$$f * x = U\big((U^T f) \odot (U^T x)\big) = U g_\varrho U^T x \tag{26}$$

Graphic convolution relies heavily on the eigenvalue decomposition of the Laplacian matrix. There is a quadratic relationship between the total amount of nodes and the computing complexity when the graph size is big. Graph convolution methods are mostly useful for small-scale networks due to the high cost of eigenvalue decomposition. Figure 3 showed in GCN model. In order to tackle this problem, Krizhevsky et al. suggested a method for approximating g_ş via Chebyshev polynomials T_k, that may be stated in the following way:

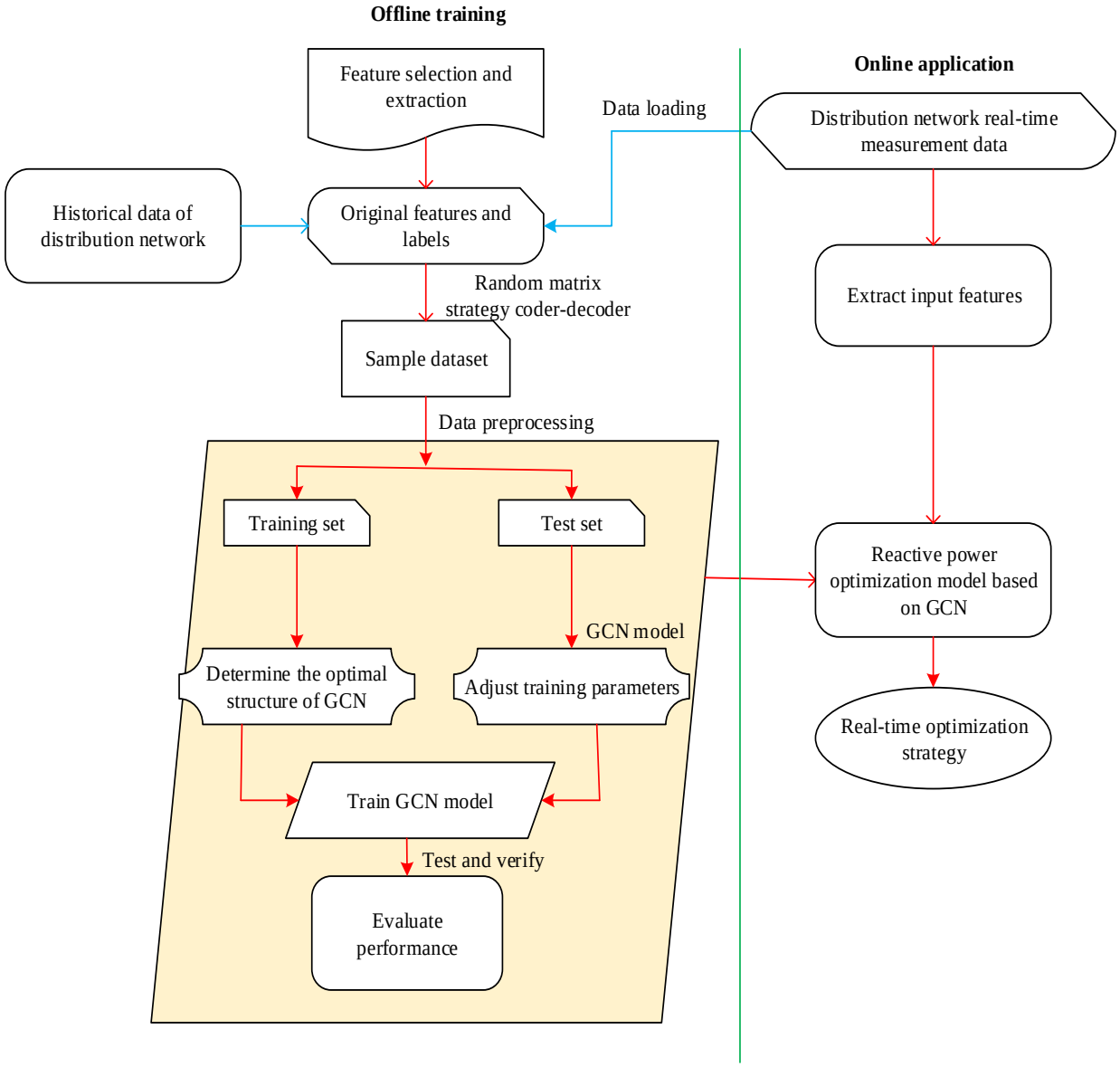

Figure 3: Proposed GCN model

$$g_\varrho(\Lambda) = \sum_{k=0}^{k-1} \theta_k T_k(\tilde{\Lambda}) \quad (27)$$

in where θ stands for the Chebyshev coefficient while T_k for the k-th element of the Chebyshev polynomial. To be more precise, it is $T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), T_o(x) = 1$, and $T_1(x) = 1.\tilde{\Lambda} = 2\,\Lambda/\lambda_{\max} - I_N$ contains the eigenvalues of scale in a diagonal matrix. Then, we may write (4) as:

$$f * x = Ug \circ U^T x \approx \sum_{k=0}^{k-1} \theta_k T_k(U\,\tilde{\Lambda}\,U^T)x = \sum_{k=0}^{k-1} \theta_k T_k(\tilde{L_m})x \quad (28)$$

where $\tilde{L} = 2L/\lambda_{\max} - I_N$ and $\lambda_{\max}$ stand for the highest eigenvalue of the Laplacian matrix. A more simplified version of the Chebyshev polynomials was developed by Xiao et al. $\lambda_{\max} = 0$ and $k = 2$, that is, the data is only aggregated from nodes that are in the first order neighboring the central node. This leads us to the following simplification of (6):

$$\begin{aligned} f * x &\approx \theta_0 x + \theta_1 \left(\frac{2L_m}{\lambda_{max}} - I_N\right) x \\ &\approx \theta_0 x - \theta_1 \left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}}\right) x \end{aligned} \quad (29)$$

By setting the parameter $\theta = \theta_0 = -\theta_1$, (7) more information about:

$$f * x \approx \theta_0 \left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}\right) x \quad (30)$$

Additionally, the settings allow the network to be trained using backpropagation " W, D^c often undergo renormalization via $\tilde{W} = W + I_N$ and $\tilde{D}_{tl} = \sum_f \tilde{W}_{tl}$, that is, in turn. Lastly, the spectral domain convolution operation is defined as:

$$f * x \approx \theta\left(I_N + D^{-\frac{1}{2}}AD^{-\frac{1}{2}}\right)x = \theta\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}\right)x \tag{31}$$

4 Result and discussion

4.1 Configuration of PV system

This study's suggested PV system is composed of a great deal of different components. A first step involves the use of a solar panel to convert solar energy into electrical energy. Through the use of a boost converter, the output voltage of the array is thus increased while simultaneously maintaining the appropriate voltage level. A DC–AC converter is provided in order to maintain a power factor of one while converting DC to AC. In addition, a transformer is used in order to raise the output voltage to the amount that is necessary for a common connection. In order to optimize power extraction, maintain a power factor of one, and modify junction voltage, the control group of the system is comprised of a number of different strategies that have gone through extensive study. In this part, the primary issues that will be discussed are the modeling of a solar power system and the performance of the system. It begins by providing an overview of the characteristics of the PV module. It covers how the photovoltaic module reacts to variations in temperature and the amount of sunlight that it receives. Another component that is included is the boost converter, which is responsible for monitoring the reduction in the output voltage of the PV array. An exhaustive amount of information is provided on the operation of the boost converter as well as its control mechanisms, which include the MPPT approach. With the help of the MPPT technology, the photovoltaic (PV) system is able to run at its maximum power output regardless of the changing environmental conditions. A DC–AC inverter is also discussed in this section. This device converts DC energy generated by a photovoltaic array into AC power for grid integration. While discussing the operation and management of the DC–AC converter, a power factor of one is maintained throughout the discussion. Within the context of this section's treatment of the modeling, performance, and control elements of the PV system, the PV module, boost converter, MPPT method, and DC–AC inverter are all dissected in great detail.

4.2 Simulation

During this section, the performance of the system was examined at a number of different levels of direct sunlight irradiation, all while maintaining a constant temperature of 25 degrees Celsius for the photovoltaic array. Standard test conditions (STC) were used in order to determine the output of the solar panels while the temperature was set to 25 degrees Celsius. The Simulink model of the photovoltaic (PV) system, which illustrates the linked components and the interactions between them. Additionally, the mathematical model that is used to explain the solar panel's electrical characteristics is included into the PV module block, which serves as a representation of the solar panel. It takes into account the input solar radiation as well as temperature in order to generate the matching current–voltage (I–V) and power–voltage (P–V) curves. It is the responsibility of the booster converter block to monitor the drop in the output voltage of the PV array. The control algorithm that is used to guide the functioning of the boost converter via the utilization of the MPPT approach is included inside it. The Maximum Power Point Tracking (MPPT) algorithm continually analyzes and adjusts the PV system's operating point in order to achieve maximum power extraction. Through the use of the DC–AC inverter block, the DC power generated by the PV array is converted into AC energy that is compatible with the grid. Furthermore, a power factor of one is assured, in addition to the maintenance of the quality and interoperability of the AC power that is produced with the utility grid. Transformers and grid connections are two examples of extra model construction parts that might be used to depict the photographvoltaic (PV) system as a whole as well as its connection to the conventional electrical grid.

Results from a two-stage PV system with a three-level inverter and a DC/DC converter that is linked to a weak grid are shown below. Results show that the control method and inverter configuration were executed when the system was evaluated under different dynamic situations. The PV array, DC/DC converter, and three-level inverter that interface with the grid is all shown Table 1, which is the system schematic. In Table 1 we see the system's parameters. Grid voltage sag, Grid voltage swell, irradiance change, and a comparison between two-levels with three-level inverters are among the operational situations that the system is evaluated under. Voltage on the grid, current via the grid, current through the VSC, current through the PV array, and the weighted positive sequence are the critical metrics studied. The stability, power quality, as well as transient responsiveness of the system under dynamic situations may be understood by examining these factors.

Table 1: System parameters

Parameters	**Value**
PV Array	55
Power Rating	35 kW
Maximum Power (W)	211.802
Short-circuit current Isc (A)	9.03
Voltage at maximum power point Vmp (V)	27.9
Cells per module (Ncell)	70
Open circuit voltage Voc (V)	39.17
Shunt resistance Rsh (ohms)	312.6345
Temperature coefficient of Voc (%/deg.C)	-0.36044
Temperature coefficient of Isc (%/deg.C)	0.112
Parallel strings	7
Series-connected modules per string	23
Boost Converter	
Inductor L_{cc} (mH)	4
Capacitor $C_{ac}(\mu\ F)$	100
Voltage Source Converter	
Interfacing Inductor $L_f(mH)$	75
$RCR_f(\Omega)$	0.4
$RCC_f(\mu\ F)$	100
Grid Voltage and Frequency, (V) and (Hz)	433, 70
DC link capacitor	2200 µF
PV array current Ipv	3.46 A
Inductance L Resistor R	2 mH 0.1 Ω
PV array voltage Vdc	540 V
Grid Frequency	50 Hz
Grid Voltage rms	120 V

The experimental environment and the recommended technique's effectiveness are described in this section. Several metrics, including power loss, grid current, voltage deviation, along with grid voltage, are used to assess the system's performance via the use of the innovative KNN-SMOTE-GCN algorithm. By redistributing loads and arranging generating units, KNN-SMOTE-

GCN systems improve the efficiency of power grids. To optimize power quality, KNN-SMOTE-GCN controllers regulate the grid's reactive power, voltage, and harmonic correction. The system is constantly adjusting the control settings using fuzzy rules with real-time data to maximize power quality.

Implementation Steps

There are various essential phases involved in the implementation process. Before anything else, it is necessary to gather historical data on demand, generation, and market pricing. Additionally, forecasting models should be used in order to make predictions about future demand, renewable generation, and market prices. In the next step, the optimization problem is stated and used in order to combine the objective function, constraints, and suitable optimization solvers, such as linear programming. or mixed-integer planning. After this, the control algorithms for the first, second, and third control levels are designed and implemented inside a hierarchical manage structure. This is done in order to further govern the system. For the purpose of testing these control algorithms and verifying that they are stable and effective, the system is then simulated under a variety of market condition scenarios. With the last step, the control algorithms are implemented for real-time operation. This means that the system constantly checks and changes the distributed power resources (DPRs) based on the data that is being collected in real time.

4.2 Comparative analysis

Table 2 illustrates the existing techniques with their description.

Table 2: Comparison techniques

Technique	Description
Active Filters	To reduce harmonic distortion and enhance power quality, active filters are a useful tool.
Wavelet Neural Networks (WNN)	• These may be used in the creation of controllers for auxiliary damping.
Artificial Neural Networks (ANNs):	• Power systems may have their dynamic responsiveness improved with the help of ANNs.
Virtual Synchronous Generator (VSG)	The grid may benefit from the inertia and damping provided by VSGs.
Deep Deterministic Policy Gradient (DDPG)	• Damping controllers may be designed with the help of DDPG.

Power loss occurs in a grid system when electrical energy, in the process of transmission and distribution, dissipates as heat. Transmission or distribution losses are other names for this occurrence. A lower current density per unit of power is a common result of increasing voltage. When the voltage or current in a three-phase circuit is not balanced between the phases. Voltage or load imbalances cause an uneven distribution of electricity, which in turn causes losses. Low power factor happens when the voltage-current relationship is not ideal. Figure 4 show that when the power factor is low, the reactive power increases, leading to higher losses in the transmission and distribution systems.

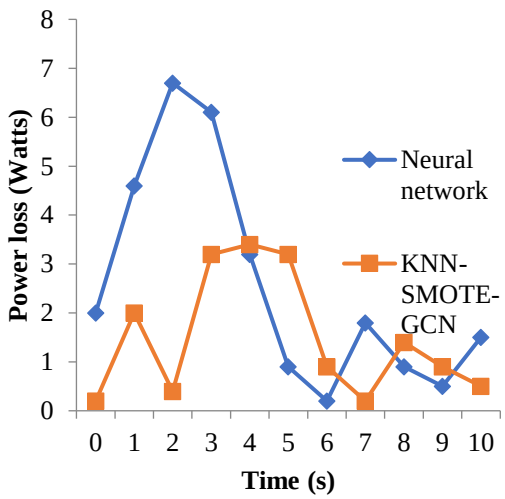

Figure 4: Power loss and time analysis

When power grid voltages deviate from their nominal or ideal values, this is known as voltage deviation. Nominal voltage standards could vary by region while kind of electrical system, although they often range from 230V to 400V and beyond. Voltage must be maintained constant and under control for grid-connected electrical gadgets and machinery to work reliably. A number of factors contribute to voltage fluctuations' potential effects on the performance and longevity of electrical devices. When the real voltage exceeds the nominal voltage, overvoltage occurs. As seen in figure 5, the term "under voltage" is used when the real voltage is less than the nominal voltage.

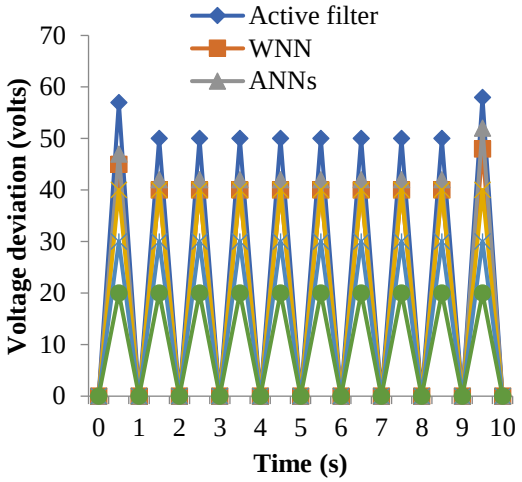

Figure 5: Voltage deviation

The efficiency, reliability, and performance of an electrical network are all impacted by fluctuations in reactive power in a grid system. Maintaining safe voltage levels and powering inductive loads both need reactive power. There are a lot of potential sources of reactive power fluctuations, which might lead to undesirable outcomes. Reactive power is a component of electrical power that does nothing useful while it sways between the generator and the consumer. "Reactive volt-amperes" is the standard measuring unit. When inductive loads are included or excluded, changes to the load profile may cause variations in reactive power. As seen in figure 6, fluctuations in generator output, especially in synchronous generators, may affect reactive power.

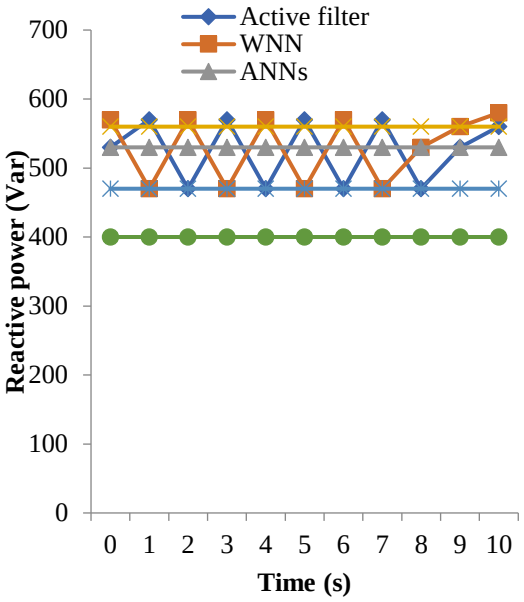

Figure 6: Reactive power fluctuation

A grid system experiences THD when harmonic components are present in the voltage or current waveform in relation to the fundamental frequency. In power systems, the fundamental frequency is typically 50 or 60 Hz, and harmonics are multiples of that. Harmonics may be caused by a variety of sources, including non-linear loads and switching operations.

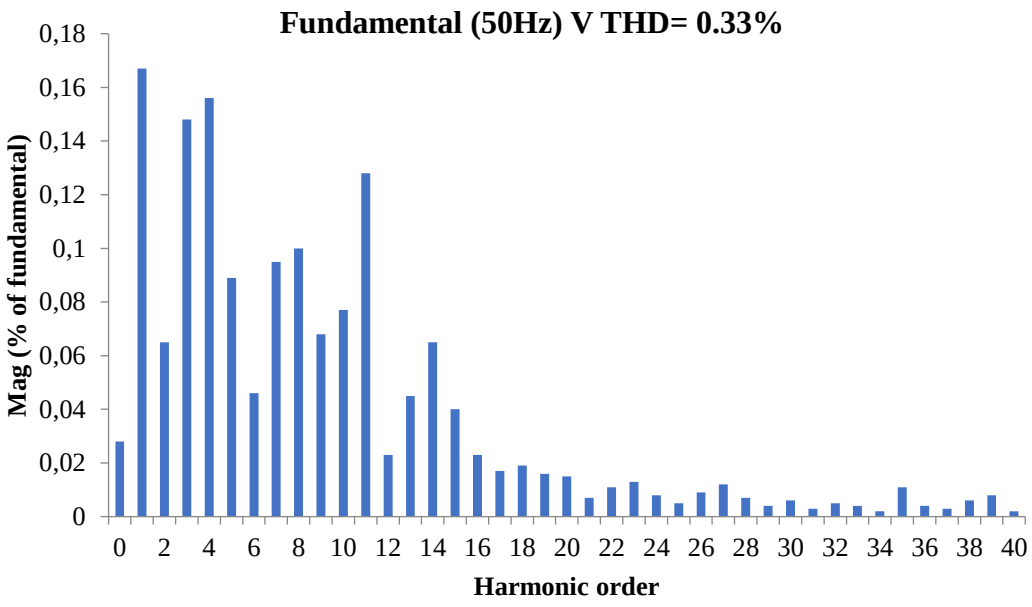

Figure 7: THD analysis

We get the THD by Figure 7 by dividing the root mean square (RMS) value of the harmonic content by the RMS value of the fundamental frequency. Typically, total harmonic distortion is expressed as a proportion of the fundamental frequency. Additionally, figure 6 shows THD in action. The performance comparison yielded better findings from the proposed work's assessment of performance. The comparative assessment has shown that the proposed model has successfully minimized the THD as much as possible. Consequently, PV systems that are linked to the grid may use it. In this study, we maximize the produced output power of the PV panel by using a DC-DC converter using MPPT. Step one involves regulating the boost converter's duty cycle. It is necessary to gradually raise the DC voltage of the PV array until it reaches a high enough voltage to meet the load's requirements. Whenever power is needed, it is transferred from the stored energy in the inductor to the load. The duty cycle, or gate pulse input, is responsible for carrying out the whole operation. It is vital to manage the duty cycle. After then, it's a matter of getting the most electricity out of the PV array in any weather. To maximize the voltage and power output of a photovoltaic array, irradiance and temperature are the two most critical elements. Therefore, it is necessary to monitor the maximum power stage, which is near the PV array's maximum power. The MPPT was created to provide a standardized, efficient tracking system. Prior research has explored a wide variety of MPPT methods for peak power tracking. Some MPPT methods, like P&O, which uses step-size control as well as

oscillates around steady state in response to dynamically changing environmental variables, have been shown to have significant drawbacks, however. The incremental conductance method is more complicated and expensive [11], [19], but it responds quickly to changing conditions. The controllers utilized in this investigation yielded promising outcomes since they were based on mathematical principles. There has been an astonishing level of consistency throughout the whole energy output, leading to a steady supply of 27 MW of pumped electricity to the grid. This is true even if the amount of sunlight reaching Earth has changed during the course of the day. Many researchers and professionals in the field have taken an interest in photovoltaic (PV) systems. The incremental conductance + integral regulator strategy is one of the methods proposed for training the MPPT controller; it is referenced. The goal of developing this method was to ensure that the photovoltaic (PV) system operates at its maximum power point in all weather conditions, thereby optimizing its performance. Also, a Proportional-Integral (PI) controller was recommended as a method for controlling the DC-AC converter in the study. The conversion of direct current (DC) from solar panels to alternating current (AC) for grid integration relies on this converter. It should be noted that various control techniques become unstable when exposed to large fluctuations in solar irradiation. Keeping energy output steady is made more difficult by the fact that solar radiation is inherently unpredictable, especially when clouds are present or when the sun's beams are changing. A change in the amount of power supplied into the system could be discernible if sun irradiation decreases. Concerns about the practical applications of PV systems, particularly those connected to the electricity grid, are highlighted by this phenomenon. Although mathematically-based controllers have performed well in conditions of relatively constant solar radiation, they may require additional tuning to account for the challenges posed by sudden and unexpected changes in solar radiation. These findings are important because they show how important it is to have adaptive control systems that can adjust to new conditions and maintain a steady power supply and stable grid. Research in this area may focus on creating more resilient and flexible solar controllers in the future by combining real-time weather forecasts with sensor-based feedback systems. To further improve the reliability of grid-connected photovoltaic (PV) system [17]s, research into energy storage alternatives like batteries may also provide a means of reducing the impact of variations in sun irradiation. Solar energy consumption might be maximized with these upgrades, which would be a huge step toward creating sustainable energy and integrating systems.

A cleaner and more sustainable energy landscape may be achieved via the total performance and efficiency of photovoltaic (PV) systems, which can be enhanced through this synthesis of current approaches. Study results were very promising for the proposed system, obtained after an exhaustive series of simulations meticulously executed on the MATLAB/SIMULINK platform. The predictive control systems utilized demonstrated remarkable robustness in the face of dynamic variations in solar radiation levels, allowing for a constant energy production profile relative to the energy production profile. Additionally, the suggested system's adaptability to rapidly changing weather conditions ensures continuous and dependable energy generation, thus establishing its status as a robust and resilient energy solution alternative. As we navigate into the future of photovoltaic (PV) systems, it is wise to direct research efforts on investigating and perfecting innovative control techniques. The overarching goal is to make the system far more efficient and productive, with an unwavering commitment to producing even more remarkable and dependable results. Furthermore, the research plan includes a comprehensive comparison study, an exhaustive endeavor aimed at methodically contrasting the effectiveness of these novel control methods with the performance metrics of the current systems. The whole capability of sophisticated control techniques is expected to be exposed by using this methodical approach. By streamlining grid connectivity, these methods are poised to change the course of renewable energy generation. Ultimately, this research adds to the growing body of knowledge on renewable energy sources by introducing a new photovoltaic (PV) system and demonstrating the system's inherent capacity to address major energy and environmental issues. This contribution demonstrates the potential of state-of-the-art control systems and optimization methodologies, building a foundation for a future that is sustainable, energy-efficient, and kind to the environment.

5 Conclusion

In order to improve grid-connected PV systems, this study presented a new KNN-SMOTE-GCN method. In this case, the UPQC model is used to enhance power quality. This model controls voltage and current concerns to assure better power quality. Beyond that, the MPPT algorithm, which controls the grid system dynamically, extracts the maximum power from solar panels. By using GCN, the grid system's MMPT and UPQC operations may be coordinated to ensure optimal power quality. Hence, power loss, voltage deviation, total harmonic distortion, and reactive power variations make up the assessment criteria. In addition, we compare the resultant parameter considerations to those of more traditional models. According to the results, the created KNN-SMOTE-GCN paradigm reduced power loss by 4% compared to the other models. The voltage deviation is 26.42V and the total harmonic distortion is 0.56THD. When applied to hybrid

renewable energy systems, DL models and optimization algorithms will improve BESS in the future.

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MDIR-BERT: A Multi-Dimensional Retrieval-Enhanced Language Model for Power Audit Text Understanding

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Keywords: Power audit text, multi-dimensional information retrieval, large language model (LLM), audit category classification, multi-dimensional information retrieval-based bidirectional encoder representations from transformers (MDIR-BERT)

Received: May 1, 2025

In the rapidly evolving energy sector, efficient access to relevant information from power audit reports is crucial for informed decision-making, regulatory compliance, and operational improvements. However, the intricate language, complex vocabulary, and unstructured format of power audit texts present significant challenges for conventional information retrieval techniques. To address these issues, the research proposes a novel power audit text understanding technology that combines multi-dimensional information retrieval enhancement with a domain-adapted Large Language Model (LLM) to enhance the performance of power audit text processing. The Multi-Dimensional Information Retrieval-based Bidirectional Encoder Representations from Transformers (MDIR-BERT) method captures electric-power-specific morphology, domain-specific vocabulary, and intricate entity relationships more effectively. MDIR-BERT is pre-trained on a huge quantity of electric power audit transcripts utilizing both word-level and entity-level covered language modeling tasks. The model is trained on a curated dataset of annotated electric power audit documents sourced from regulatory and industrial environments. MDIR-BERT integrates domain-specific pre-training with both word-level and entity-level masked language modeling, capturing electric power-specific morphology, terminology, and complex entity relationships. The data preprocessing steps include comprehensive text cleaning, normalization, and tokenization to ensure high-quality input for method training. Experimental results show that MDIR-BERT achieves a classification accuracy of 98.82%, representing a +16.86% improvement over the baseline EPAT-BERT model (81.96%), along with notable gains in precision, recall, and F1-score. These findings highlight the effectiveness of integrating enhanced information retrieval techniques with specialized language modeling for the intelligent understanding of power audit documentation, paving the way for more accurate, scalable, and interpretable audit methods.

Povzetek: MDIR-BERT, izboljšan jezikovni model s večdimenzionalnim iskanjem informacij (MDIR), je razvit za razumevanje revizijskega besedila elektroenergetike. S predhodnim usposabljanjem na besedni in entitetni ravni dosega kvalitetno klasifikacijo revizijskih kategorij.

1 Introduction

The development of Information Retrieval (IR) technology has been intimately linked to the human need for information access. In recent years, IR and associated product systems have expanded significantly as a critical constituent of smart data dispensation tools. The basis of IR technology is the identification of documents related to the customer's search from a big and unorganized collection, which usually leads to a graded catalog of the documents by significance and user requirements [1]. IR plays an essential role in numerous real-world functions, like expert finding, digital libraries, and Web search. IR essentially refers to the task of retrieving information resources related to information required from a large collection of resources [2]. However, user intentions were more complex than simply retrieving information based on similarity [3]. This audit is conducted by a qualified firm with the necessary competencies in line with the requirements established by the Ministry of Energy and Mineral Resources. These criteria apply to businesses or industries that utilize a significant amount of energy. A complete audit evaluates all areas of energy usage, from fuel consumption to the use of generated electrical energy [4]. Lowering electricity costs and cutting down energy waste requires an energy audit. Efforts have to be initiated by governments to require periodic energy audits for industrial buildings. An energy audit is a great way to find the best solution and

assess how much energy a building uses [5]. The generative probability of word sequences, or more generally, the ability to predict forthcoming words conditional on prior words, is a crucial function of language models (LM). LMs were first created for text creation, but they are also being studied for reformulating
a range of NLP issues into different text-to-text challenges in the text of electric power audits [6].
The implementation of Large Language Models (LLMs) marks the most important change in the technical development of electric power audit text [7]. LLMs mark a substantial advancement in Artificial Intelligence (AI) as it makes breakthroughs in generalization and adaptability across tasks, but LLMs generate inaccurate information, misalign with temporal information, struggle to keep context, and struggle to fine-tune each response, leading to serious issues regarding reliability when applied to electric power audit text [8]. In the continually changing energy industry, timely access to essential information from power audit reports is critical for making informed decisions, conforming to regulations, and improving operations. Conventional BERT-based models are not effective in encoding the sophisticated, domain-specific semantics in electric power audit reports. There is a demand for models incorporating domain knowledge and sophisticated retrieval methods to enhance classification and information extraction accuracy. This research explores a new technology for understanding power audit reports that improves multi-dimensional IR and domain-adapted LLM performance by extracting morphology specific to electric power, domain-specific language, and complexities of entities to use the Multi-Dimensional Information Retrieval-based Bidirectional Encoder Representations from Transformers (MDIR-BERT) method.

1.1 Key contributions

- This research aims to develop a multi-dimensional information retrieval for improved classification and understanding of electric power audit texts.
- Initially, Electric power audit reports from energy-intensive sectors, which are obtained from publicly accessible databases from Kaggle, represent various regulatory and operational contexts.
- Utilized preprocessing steps such as stop word elimination, lemmatization, and tokenization to preprocess and normalize intricate technical jargon for optimal model input.
- MDIR-BERT by pre-training on the electric power audit dataset with word-level as well as entity-level masked language modeling to encode domain-specific terminologies and intricate entity relationships.
- Obtained a classification accuracy of 98.82%, representing a +16.86% relative improvement compared to the baseline EPAT-BERT model, in addition to significant boosts in precision, recall, and F1-score.

1.2 Research questions

RQ1: Can a domain-adapted BERT model (MDIR-BERT) enhanced with multi-dimensional information retrieval outperform general-purpose BERT (EPAT-BERT) in power audit text classification?
RQ2: How does multi-dimensional information retrieval improve entity recognition and contextual understanding in regulatory audit texts?
RQ3: What impact does domain-specific pretraining have on the performance of language models in complex, unstructured audit document processing?
The research outline is organized as follows: Section 2 reviews related research, while Section 3 outlines the research methodology. Section 4 presents the results and discussion, and Section 5 concludes the research.

2 Related work

The transformational effects of LLMs on IR research were investigated in the research [9]. The method comprised synthesizing findings from a strategy workshop organized by the Chinese IR community. It suggested a new IR technological paradigm involving IR models, LLMs, and humans, but faces computational trade-offs, trustworthiness concerns, domain boundaries, and implications. An analysis of e-commerce customer reviews on drum washing machines using Robotic Process Automation (RPA) was demonstrated [10]. It combined ROST Content Mining System 6 (ROSTCM6) and LOGCONTROL-BLOCK systems to extract sentiment and correct audit robot paths. While effective in revealing customer sentiments and guiding e-commerce strategies, limitations include reliance on predefined keywords and the need for improved automated sentiment analysis accuracy.
The Mistral 8x7B LLM's current Mixture of Experts (MoE) architecture was combined with Retrieval Augmented Generation (RAG) to improve on challenging IR and reasoning tasks, which were investigated in [11]. In the quantitative and qualitative evaluation of the model using the Google BIG-Bench dataset, notable gains were observed in F1 score, accuracy, precision, and recall. Limitations include computing needs and dataset breadth. Integrating LLMs with Knowledge Graphs (KGs) enhanced intelligent fault detection and IR for new energy vehicles (NEVs) [12]. It developed an intelligent fault retrieval system, a structured knowledge graph, and an optimized BERT model for fault classification,

demonstrating exceptional performance in Q&A situations for NEVs, but facing scalability issues.

To evaluate the Word to Vector (Word2Vec) model for document compliance detection by comparing it with Term Frequency–Inverse Document Frequency (TFIDF), Latent Dirichlet Allocation (LDA), and Bidirectional Encoder Representations from Transformers (BERT) as described [13]. Results showed that Word2Vec effectively captures semantic similarity with higher efficiency and simplicity. However, it performs slightly lower than BERT in handling complex semantics and domain-specific terminology. A self-retrieval framework [14] that leverages self-supervised learning was developed to improve retrieval efficiency and model simplicity. It internalized a retrieval corpus, improved downstream LLM applications, and outperformed conventional IR systems. However, it faced high computing costs and scaling challenges, despite maintaining real-time efficiency and cross-domain generalizability. Predictive Analytics (PA) in Current Research Information Systems (CRIS) to predict research trends through machine learning is used [15]. In this research, k-Nearest Neighbor had the best performance. Limitations include moderate AUC scores and dependence on historical metadata to generate predictions. The Financial BERT (FinBERT) model, specialized in the finance industry, was developed to enhance sentiment analysis in financial writings [16]. FinBERT model outperformed traditional dictionaries in classifying context-dependent sentiment and Environmental, Social, and Governance (ESG)-related talks with minimal training data, but faced limitations in domain-specificity and potential decreased generalizability. The use of LLMs in auditing was investigated in [17], with an emphasis on compliance checks and report production. LLMs effectively handle unstructured data, address compliance concerns, and provide excellent audit reports, despite challenges like data security and model interpretability. The research [18] enhanced LLM privacy audits by creating more robust sequences that allow for more successful membership inference assaults under realistic threat models. It demonstrated a significant improvement in detection and True Positive Rate (TPR) with optimal sequences, achieving a 49.6% TPR on Qwen2.5-0.5B, compared to 4.2% earlier, but has drawbacks due to reliance on model access without shadow models or gradient insertion. To compare forecasting MASI trends with ARDL with trend and seasonality (Long short-term memory (LSTM), and extreme gradient boosting (XGBOOST) was determined [19]. ARDL, with trend and seasonality, returns the lowest MAPE, at 26.7%. Limitations include LSTM and XGBOOST executing higher error rates and taking longer to process. The Two Sliding Windows Graph Neural Network (TSW-GNN) architecture for text classification was introduced, which works around limitations of corpus-level graph approaches that suffer from continuous memory usage and are completely contextually agnostic, was introduced [20]. The TSW-GNN model addresses this issue by introducing TSW into the GNN architecture with a new dynamic global sliding window and a new dynamic local sliding window, increasing contextual memory and representation of semantics. Tests from the seven datasets reveal that the classification accuracies were improved, though at increased complexity of the two sliding windows and their associated GNN parameters. To explore the independent role of internal auditors at the Swedish Police Authority and to illustrate their relational struggles within the organization was described [21]. The research adopts a narrative framework in the study of auditor independence and introduces stories of auditors highlighting psychological distress, ambiguity in legitimacy, and attempts to negotiate competing demands. The picture painted by these narratives can be viewed as a tragedy where auditors were unable to resolve tensions that manifested themselves as professional dilemmas. Results showed LLMs perform well in noise handling but struggle with falsehood management. An overview of the related work is given in Table 1.

Table 1: Overview of the related works

Ref. No.	Objective	Task Type	Domain	Model Used	Method	Limitations
Ai et al., [9]	Investigate the role of LLMs in IR research	Information Retrieval	General	Not specified	Strategic workshop proposing IR-LLM-human paradigm	Computational trade-offs, trust concerns, and ethical issues
Sun and Huo, [10]	Analyze e-commerce reviews using automation	Sentiment Analysis	E-commerce	RPA, ROSTCM6, LOGCONTROL-BLOCK	Keyword extraction, path correction, sentiment classification	Relies on predefined keywords, limited sentiment accuracy

Xiong and Zheng, [11]	Improve IR and reasoning	IR + Reasoning	General	Mistral 8x7B with RAG	RAG + Mixture of Experts evaluated on BIG-Bench	High computing needs, limited dataset
Zhang et al., [12]	Enable intelligent IR for NEVs	Classification + Retrieval	New Energy Vehicles	Optimized BERT + KG	Fault classification using KG-enhanced BERT	Scalability issues
Wen et al., [13]	Evaluate Word2Vec for document compliance detection	Document Similarity	Legal, Audit	Word2Vec, TFIDF, LDA, BERT	Semantic similarity via vector models	Slightly lower performance than BERT in complex semantics
Tang et al., [14]	Merge IR functionality within a single LLM	IR	General	Self-Retrieval LLM	Self-supervised corpus-internal IR	High computational cost, scaling complexity
Azeroual et al., [15]	Predict research trends in CRIS	Trend Forecasting	Research Management	kNN, SVM, Random Forest	Predictive analytics with machine learning	Moderate AUC, dependent on historical metadata
Huang et al., [16]	Domain-specific sentiment analysis	Sentiment Classification	Finance	FinBERT	Domain-adapted BERT for financial sentiment	Limited generalizability
Gan, [17]	Automate audit compliance	Report Generation + Classification	Auditing	LLM-based	Process unstructured audit data for reporting	Data security, interpretability
Panda et al., [18]	Enhance privacy auditing	Membership Inference	General	Qwen2.5-0.5B	Robust canaries for audit testing	Requires model access, no shadow models
Oukhouya et al., [19]	Compare forecasting models for MASI trends	Financial Forecasting	Stock Market	ARDL, LSTM, XGBOOST	Time series modeling with trend and seasonality	Higher error and processing time in LSTM and XGBOOST
Li et al., [20]	Improve text classification with sliding windows	Text Classification	NLP	TSW-GNN	Local and global sliding window graph construction	Increased model complexity and parameter tuning
Nordin et al., [21]	Explore internal auditors' independence challenges	Organizational Behavior Analysis	Public Sector / Audit	Narrative Framework	Story-based analysis of auditor roles	Unresolved tensions, emotional strain, and ambiguous legitimacy

Existing approaches have various difficulties, including computational complexity, ethical problems, scaling challenges, decreased accuracy, a limited dataset scope, low generalizability, data security threats, and reliance on embedding quality. These constraints impede real-time, domain-specific, and reliable information retrieval in specialist sectors, such as electric power auditing. To address these issues, the research explores a new technology for understanding power audit reports that improves multi-dimensional IR and domain-adapted LLM performance by extracting morphology specific to electric power, domain-specific language, and complexities of entities to use the MDIR-BERT Model.

3 Multi-dimensional information retrieval (MDIR)

MDIR is an advanced retrieval technique that expands the traditional keyword-based search into a multidimensional framework, incorporating semantic meaning, contextual relevance, domain-specific lexicon, relationships between entities, and user intent, thereby enabling retrieval that is precise and comprehensive. MDIR increases the power of a text understanding process for audit text, allowing for the MDIR-BERT model to better capture the complex, technical, unstructured nature of power audit documents and their underpinning. This section gathers the electric power audit text data and preprocesses the data using techniques, such as data cleaning using Stop Words Removal and data normalization using lemmatization and tokenization. Finally, classification and information retrieval were performed using BERT. Figure 1 depicts the System Design of the MDIR-BERT Model.

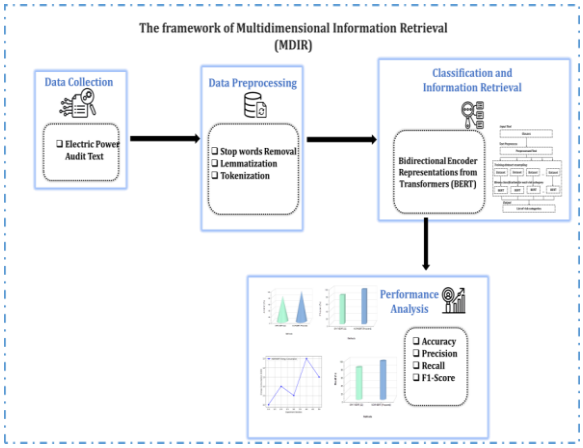

Figure 1: System design of the multi-dimensional information retrieval-enhanced BERT model

3.1 Data collection

The data is obtained from the Kaggle link: https://www.kaggle.com/datasets/zoya77/power-audit-report-and-entities-dataset. The dataset comprises 1,001 audit report entries collected from Kaggle. Each entry includes an audit report ID, audit text, a list of extracted named entities, and a category label. The technical power audit reports cover equipment, energy systems, and compliance, supporting tasks like entity recognition and classification across categories such as safety, efficiency, and regulation. Audit texts range from 15–40 tokens, averaging around 25 tokens. Entities cover standard equipment (e.g., Load Balancer) and locations (e.g., Control Room), enabling comprehensive analysis of energy systems. The obtained dataset is split in 80:20 ratios for training and testing performance.

3.2 Data preprocessing

Data preprocessing is the procedure of converting fresh data into an organized and cleansed form to improve model performance. It cleans, normalizes, and tokenizes electric power audit texts to provide high-quality input for model training while also improving classification and information retrieval accuracy. It includes approaches, such as stop word removal, lemmatization, and tokenization, to arrange power audit texts in a structure that reduces noise while providing high-quality information. It allows for efficient and accurate IR, entity recognition, and classification operations in the system.

3.2.1 Data cleaning using stop words removal

Data cleaning is the process of removing unnecessary or noisy elements from raw data to make it more accurate. It is utilized to eliminate extraneous or noisy information, resulting in high-quality input for training and improved overall performance of electric power audit classification. In the research, stop word removal reduces frequent, unnecessary words from audit text so that the model focuses on important content for better IR and classification. This is produced by establishing a frequency threshold. This threshold was simply set as the average frequency of all terms gathered for the language in Equation (1).

$$\sigma = \frac{\alpha}{n}\sum_{j=1}^{n} t_j \qquad (1)$$

Where t_j is the frequency of the j^{th} term, Equation (1), α is defined as a smoothing adjustment factor to 1.25, empirically validated in validation experiments to moderately increase the average threshold and dampen noise from low-frequency terms. This value $\frac{\alpha}{n}\sum_{j=1}^{n} t_j$selected to optimize in entity recognition by preventing inclusion of excessively rare or excessively common terms.

3.2.2 Data normalization using lemmatization

Normalization refers to the process of converting text to a uniform state, often by reducing words to their standard forms or original structures. The normalization process allows the different variations of words to be standardized,

which permits the method to better process and comprehend province-precise language in power audit texts. This process of normalization helps to standardize variations of words to allow for treating different versions of a word as equivalent terms. Lemmatization helps to determine the organizational meanings of words, which assists in the analysis of text, and naturally, the processing of this text. It is valuable in many text analysis projects, especially those focusing on IR, sentiment, and text classification.

3.2.3 Tokenization

It is the procedure in which input text is divided into minor units of meaningful units (tokens), which can be meaningful individual words, phrases, or sentences. Tokenization is a key step towards breaking down the raw power of the audit text into portions that will ultimately be meaningfully analyzed by the model. By tokenizing text, the model can better interpret the relationships, structure, and contextualization of words. Tokenization will be used to confirm the conducting of tasks, like IR and entity recognition, where tokens are identified and labeled. It enhances the ability of the model to yield valuable and informative information from sophisticated and complex unstructured audit documents.

3.3 Classification and information retrieval using bidirectional encoder representations from transformers (BERT)

Classification is the process of assigning text data into predefined categories based on its content, and IR is the task of finding and extracting significant data from a huge collection of structured or unstructured information. In the research, classification helps to organize and label power audit texts into specific, meaningful categories for easier analysis, while IR enables quick and accurate extraction of relevant insights from large volumes of audit documents to support informed decision-making. These methods are boosted by BERT, which captures deep contextual power and meaning of the text to enhance classification accuracy as well as retrieval precision. After tokenization, BERT uses the electric power audit text to gather contextual relations for accurate classification. It further enhances IR through accurate detection and retrieval of audit-specific features and patterns.

3.3.1 Overview of MDIR-BERT

MDIR-BERT is based on the basic architecture of BERT (Bidirectional Encoder Representations from Transformers), which encodes the bidirectional context of words in a sentence through self-attention mechanisms. This helps the BERT model comprehend word semantics concerning the previous and next words, and hence, BERT is very effective for tasks like classification and information retrieval. While general BERT is pre-trained with the Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) tasks on general corpora, MDIR-BERT takes this further by adding domain adaptation for the electric power audit domain. In particular, MDIR-BERT is additionally pre-trained on a massive dataset of electric power audit transcripts to capture more domain-specific vocabulary, morphological forms, and intricate named entity relations. To facilitate this domain-specific adaptation, two domain-specific pre-training tasks are utilized: Word-Level Masked Language Modeling (W-MLM), likewise the standard MLM, but with modifications to focus on domain tokens that usually appear within audit texts, including audit procedures, voltage types, compliance, and equipment-related terms. Entity-Level Masked Language Modeling (E-MLM): This task entails masking named entities determined through a domain-tuned NER system and having the model predict them in their respective contextual environments. This assists MDIR-BERT in capturing hierarchical and relational dependencies between domain-specific entities more effectively. With these enrichments, MDIR-BERT gains a better grasp of electric-power-specific semantics and structure for more accurate and context-sensitive classification and retrieval.

3.3.2 BERT for classification

BERT processes input text using its transformer layers while performing categorization jobs. After the text has been analyzed, the output representation is sent through a classification head to forecast the text's proper category, as shown by Equation (2).

$$Output_{class} = Softmax(Dense(BERT(Input))) \quad (2)$$

Where $BERT(Input)$ represents the BERT model processing the input text, $Dense$ is the classification layer, and $Softmax$ is used to transform logits into probabilities for classification.

3.3.3 BERT for information retrieval

BERT is used in IR to discover the documents that are relevant to a given query. BERT recognizes the context of a query and a group of documents, which improves retrieval accuracy. BERT's bidirectional nature assists in identifying more semantically relevant documents even when keywords fail to match perfectly, as shown by Equation (3).

$$Relevance\ Score = Similarity(BERT(Query), BERT(Document)) \quad (3)$$

Where $BERT(QUERY)$ and $BERT(Document)$ are the query and document's context-aware embeddings, respectively.

3.3.4 Fine-Tuning BERT

Fine-tuning is the method of modifying the pre-trained BERT model to a precise goal, such as classification or IR, by training it on a labeled dataset. This involves adapting BERT's weights by the task requirements, enabling it to learn domain-specific jargon and nuances represented by Equation (4).

$$Loss = \sum_{j=1}^{N} Cross - Entropy(True_j, Predicted_j) \quad (4)$$

Where $True_j$is the definite tag for the j^{th} model, $Predicted_j$ is the forecasted tag for the j^{th}sample, and $Cross - Entropy$ is the loss function used during training. BERT has the advantage of considering the complete background of words in a phrase, which significantly enhances classification and IR efficiency. This two-way context enables BERT to recognize subtle semantic links, making it particularly useful for processing complex and specialized language in power audit reports. Furthermore, due to its pre-training on great corpora and fine-tuning capabilities, BERT could be trained to perform specific tasks with less data.

4 Results and discussion

The research objective is to improve electric power audit text categorization and IR performance by introducing a new MDIR-BERT model. The experimental setting and performance assessment measures used in the research improve the electric power audit text categorization and IR performance.

The experiments were run on a machine with an Intel Core i7 processor, 32GB RAM, and an NVIDIA RTX 3080 graphics card. The models were run in Python 3.9 with PyTorch as the base, with the BERT model developed atop this framework.
The model proposed took around 4.2 hours for training, using 4.2 GPU hours. It comprises about 110 million parameters and occupies a storage size of 420 MB. All the models were trained under the same settings to ensure fairness when comparing the process.

4.2 Hyper-parameters

Table 2 represents the hyperparameters utilized in the power audit text understanding research.

Table 2: Hyperparameters

Hyperparameter	Value
Learning Rate	$2e-5$
Batch Size	32
Number of Epochs	30
Optimizer	AdamW
Warmup Steps	500
Max Sequence Length	128
Gradient Clipping	1.0
Weight Decay	0.01
Random Seed	42
Dropout Rate	0.1

4.3 Performance metrics

The Performance Metrics, including Execution time, Energy consumption, and speed of convergence, are utilized to enhance the performance of electric power audit text classification.

- **Energy consumption**

Energy consumption refers to the energy needed by a model to execute inputs and generate outputs. It is an important metric in energy-limited systems, like internet-enabled edge devices or mobile devices. Lower energy usage renders the system more efficient and sustainable, particularly for large-scale AI deployments. Figure 2 depicts the Energy Usage seen in the MDIR-BERT Model Execution.

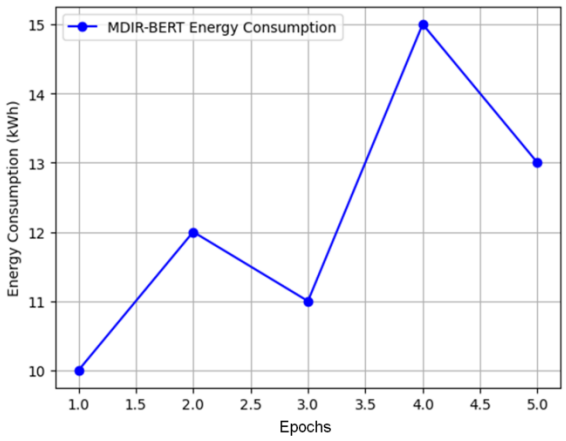

Figure 2: Energy Consumption Observed in the MDIR-BERT Model Execution

MDIR-BERT model energy consumption or moderate consumption rates varied between 10 and 15kWh over five test repetitions, which converts to moderate consumption of resources. In the central sets of repetition, there was an increase in utilization, attributed to the complexity in processing or the size of the data. The model's average utilization was more uniform and efficient, demonstrating its potential for real-world applications. For epoch 1, the model reaches 10kWh, 12kWh in epoch 2, 11kWh in epoch 3, 15kWh in epoch 4, and 13kWh in epoch 5. The proposed MDIR-BERT method shows extreme performance in epoch 4 with 15kWh.

Execution time

Execution time refers to the number of times it takes a model to consume an input, process it, and produce an output. It is a significant metric for real-time or time-sensitive applications, like autonomous systems or internet applications. Lower execution times are preferable so that users can experience the best, and the system's efficiency is enhanced overall. Figure 3 illustrates the visualization of the MDIR-BERT's execution time.

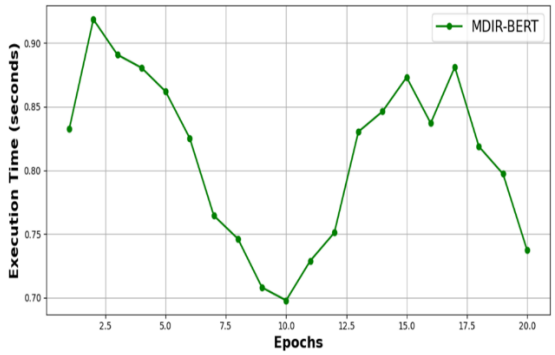

Figure 3: Visualization of the execution time of the MDIR-BERT

The execution time of the MDIR-BERT model replicates its performance over 20 epochs with moderate variances due to computation and environmental conditions. The execution duration varies around an average of 0.8 seconds, with peaks reaching roughly 0.89 seconds and troughs around 0.72 seconds, driven by a sinusoidal pattern and small random noise.

Accuracy and loss

Accuracy is the number of correct predictions made by a classical model to the total number of predictions, whereas loss is the difference between expected and actual values, which measures how well the model performs throughout training. The loss curve shows how the model converged during training, with lower values representing better performance, while the accuracy curve shows how well it captures electric-power-specific morphology, domain power, and intricate entity relationships more effectively. The accuracy and loss characteristics of the training for the MDIR-BERT technique are shown in Figure 4.

The resulting MDIR-BERT model demonstrates good performance: training loss goes down from 0.95 to almost 0.01 after 30 epochs, and training accuracy increases steeply from 0.1 to about 0.97, which indicates good convergence and high learning efficiency.

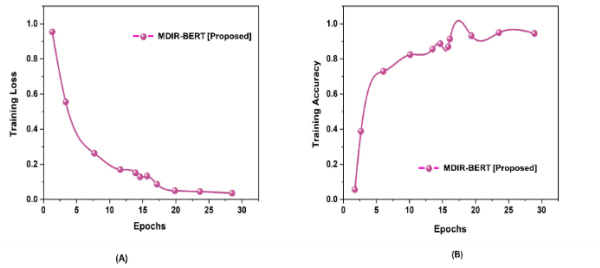

Figure 4: Graphical outcome of (a) loss and (b) accuracy

Statistical Significance

The confidence interval for model accuracy is the normal distribution curve, where the shaded region highlights the most likely accuracy range. It visually represents the reliability and accuracy of the model's performance estimate. Figure 5 shows the Graphical outcome of a 95% confidence interval for accuracy (MDIR-BERT).

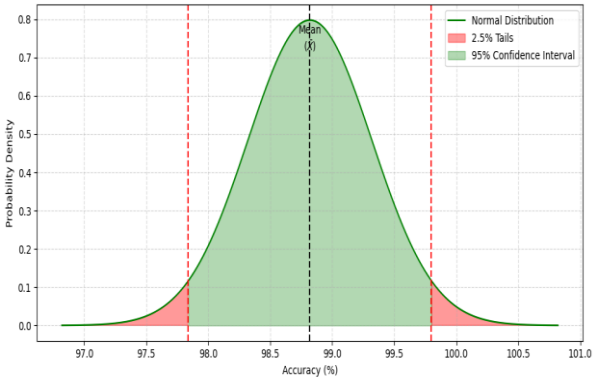

Figure 5: Graphical outcome of 95% confidence interval for accuracy (MDIR-BERT)

The image shows a 95% confidence interval for the accuracy of MDIR-BERT, represented as a normal distribution curve. The x-axis indicates accuracy percentages ranging from 97.0% to 101.0%. The shaded area under the curve represents the 95% confidence interval, meaning there is a 95% probability that the true accuracy of the model lies within this range. The 2.5% tails on either side of the distribution are excluded, highlighting the central 95% region. The peak of the curve corresponds to the most probable accuracy value, with the density decreasing as values move away from the center.

Confusion Matrix

A confusion matrix compares the expected and actual values for a dataset to show the effectiveness of a classification model (Figure 6). The confusion matrix shows how well MDIR-BERT classified data in five different power audit categories. Considering its high overall prediction accuracy, the model occasionally

misclassifies objects, especially between closely similar classes like "Energy Efficiency" and "System Upgrade." Through multi-dimensional information retrieval and domain-adapted language modeling, this demonstrates the domain complexity and the model's efficacy in comprehending electric power audit material.

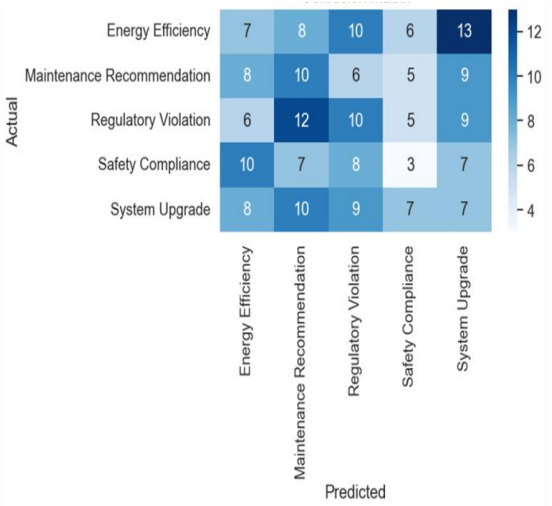

Figure 6: Confusion matrix of MDIR-BERT performance

Precision-recall curves

A binary classification model's effectiveness is represented graphically by a Precision-Recall curve, which is particularly beneficial for unbalanced datasets (Figure 7). The precision-recall curve validates MDIR-BERT's efficacy in domain-dependent audit text understanding by demonstrating its superior classification performance in power audit categories, with an average accuracy. Whereas the energy efficiency is 0.89, the maintenance recommendation is 0.91, the regulatory violation is 0.96, safety compliance is 0.97, and the system upgrade is 0.89.

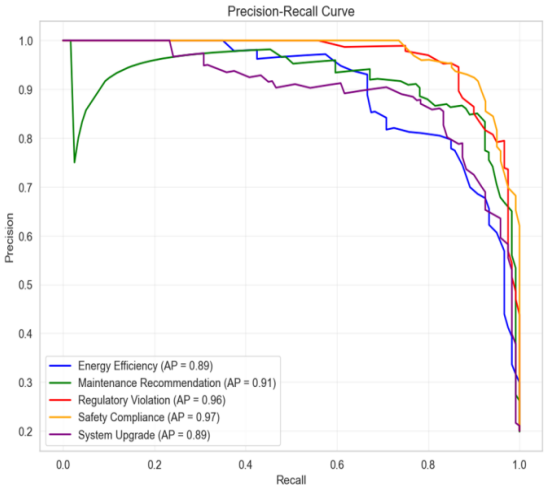

Figure 7: Efficiency of MDIR-BERT with precision-recall curves

The research evaluates the macro/micro F1. Evaluating all classes equally, Macro F1 computes the F1 score for each class separately before the results. To create a single F1 score, Micro F1 provides all the real positives, incorrect positives, and incorrect negatives for each class, which gives each occurrence equal weight. The proposed model demonstrates 0.964 of macro F1 and 0.963 of micro F1.

4.4 Comparison phase

The performance metrics used to compare the performance of electric power audit text classification are accuracy, F1-score, recall, and precision. The MDIR-BERT was compared with the existing methods like Text Convolutional Neural Networks (Text CNN) [22], BERT [22], and Electric Power Audit Text–BERT (EPAT-BERT) [22].

Accuracy

Accuracy: Accuracy indicates how well the model accurately recognizes relevant and irrelevant information in the power audit text. To indicates the ratio of correct to incorrect predictions across all cases, giving a total view of classification performance across different audit documents. Accuracy measures the proportion of all correct power audit text classifications performed by a model. It can be helpful in assessing overall MDIR-BERT's performance. Table 3 depicts the accuracy of the MDIR-BERT.

Table 3: Performance summary of MDIR-BERT

Methods	**Accuracy (%)**	**Recall (%)**	**Precision (%)**	**F1-score (%)**
Text CNN [22]	71.65	69.01	74.27	71.56
BERT [22]	77.91	77.94	78.23	78.08
EPAT-BERT [22]	81.96	81.62	80.79	81.20
MDIR-BERT [Proposed]	**98.82**	**97.81**	**96.48**	**97.34**

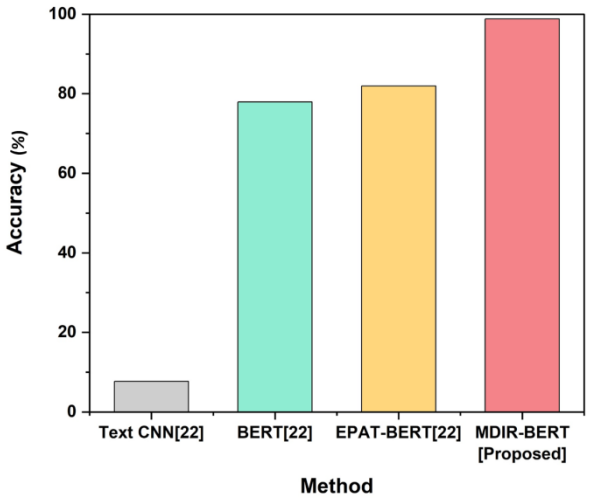

Figure 8: Graphical representation of accuracy for the MDIR-BERT

Figure 8 demonstrates consistent improvement in accuracy, which improves to 71.65% for Text CNN, 77.91% for BERT, and 81.96% with EPAT-BERT. The proposed method receives a significant increase to 98.82%, suggesting that power audit texts are classified very well overall.

Recall

Recall represents how well the model collects all the relevant audit information in the documents. Recall fits with a focus of reducing missed important content, which is key to holistic regulatory compliance and decision support in power audit. Recall is the ratio of True Positives (TP) to TP with the False Negatives (FN). Recall is important if the cost of misclassifying a positive instance is high, as in the case of a diagnostic method.

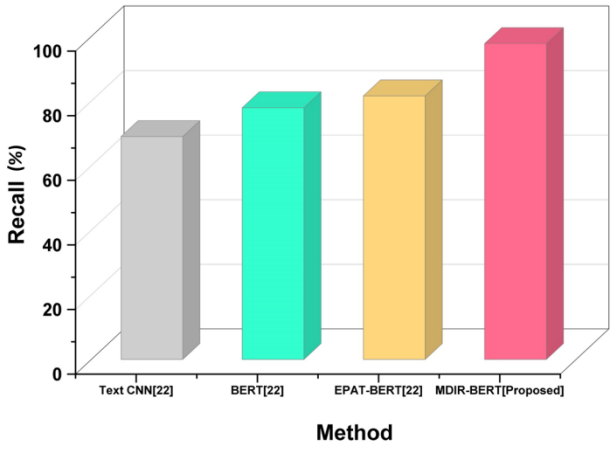

Figure 9: Visual depiction of classification recall achieved by MDIR-BERT

Figure 9 indicates the extent to which each model identifies all relevant content. Text CNN (69.01%) and BERT (77.94%) demonstrate moderate ability to identify relevant content, while EPAT-BERT shows a refined ability (81.62%), and the proposed method achieved 97.81%.

Precision

Precision assesses the extent to which each piece of text identified as relevant contains useful audit content. That is, it signifies the degree to which the model is able to avoid false positives and is a matter of importance for limiting irrelevant or misleading content through audit analysis. Precision measures the number of true positives (TP divided by the total number of TP, with the False Positives (FP). Precision is important if the cost of an FP is high, for example, misclassifying a legitimate user as a spammer or a fraudster.

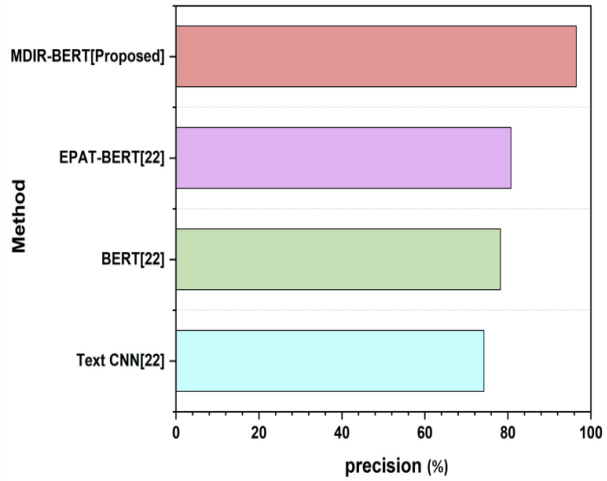

Figure 10: Precision analysis chart of MDIR-BERT model

Figure 10, indicating the correctness of predicted relevant pieces of information, is highest for the proposed method at 96.48%. This demonstrates a low false-positive rate. In the study, a measure of the precision could be performed with Text CNN, showing a decent 74.27%, BERT achieving a better performance of 78.23%, and EPAT-BERT showing 80.79%.

F1-Score

The F1-score balances precision and recall to deliver a single metric of model performance at comprehending an audit text. It can be especially helpful when it is as important to avoid false alarms as it is to capture every detail necessary. The F1-score is the harmonic average of recall and precision, which balances $precision$ and $recall$. It is especially useful in problems involving imbalanced data, especially when FP and FN are equally important.

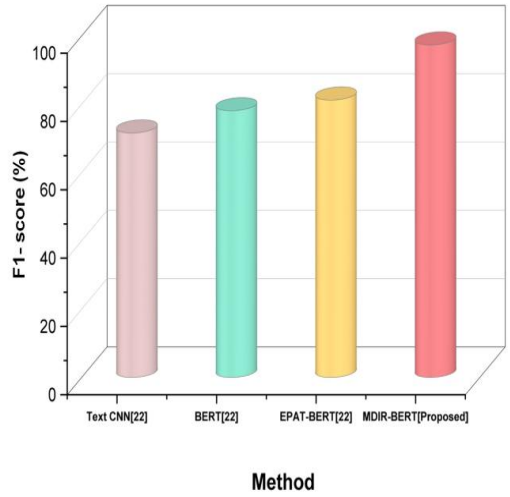

Figure 11: Performance visualization of MDIR-BERT in terms of F1-score

Figure 11 summarizes overall performance, balancing recall and precision. It ranges from 71.56% (Text CNN) to 78.08% (BERT) and 81.20% (EPAT-BERT). In contrast, the proposed method is 97.34%, and affirms our approach's clear superiority in accurately and consistently extracting meaningful audit content.

4.5 Training and testing splits

The training and testing validation of the proposed MDIR-BERT method's performance in 80:20 validations is compared with 70:30 splits to determine the efficiency of the proposed model in the field of power audit text understanding research. Table 4 explores the training and testing validation of the proposed model with 80:20 and 70:30 splits.

Table 4: Performance of proposed MDIR-BERT model with training and testing splits

Metrics	Training and Testing splits	
	80:20	70:30
Accuracy (%)	98.82	97.6
Precision (%)	96.48	95.5
Recall (%)	97.81	96.72
F1-score (%)	97.34	96.13

Based on the performance of various training and testing validations, the proposed MDIR-BERT model shows more significance in 80:20 validations than in 70:30 validation assessments.

The comparative results showed notable weaknesses in Text CNN [22], BERT [22], and EPAT-BERT [22] in their suitability to power audit text classification. Text CNN struggles with long-distance/contextual knowledge and domain-specific vocabulary and language due to its inability to layer information in a multi-dimensional way. Thus, Text CNN [22] will return lower recall and precision for this corpus. BERT [22] improved contextual understanding but did not adapt to the language structures and entities specific to power audits, which ultimately limited its performance on complicated auditor narratives. While EPAT-BERT [22] is adapted for domain use, it does not sufficiently model multi-dimensional relationships and detailed audit semantics. MDIR-BERT is superior to EPAT-BERT by the pretraining within a domain and multi-dimensional information retrieval (IR) boost, allowing for more in-depth electric power audit language comprehension and enhanced entity/context identification. It's a +16.86% accuracy improvement, indicating enhanced classification and retrieval. Whereas the success of the model is domain-specific and will not generalize to other audit types unless the model is retrained. In contrast to domain-specific transformers (such as FinBERT) and RAG-based models, MDIR-BERT has better structured text understanding but without the generative ability. Future research will focus on RAG integration for summarization and improving cross-domain adaptability by transfer learning or model compression. The proposed MDIR-BERT method in the research makes it possible for researchers, utilities, and regulatory organizations to modify and evaluate models for certain auditing conditions while providing innovation. High-stakes audit environments are secured by compliance with energy regulations and data management systems.

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5 Conclusions

The aim was to build a multi-dimensional information retrieval for enhanced classification and comprehension of electric power audit texts. MDIR power audit text comprehension technology using the integration of multi-dimensional enhancement and a domain-adapted LLM. An end-to-end data preprocessing method was utilized, which involved data cleaning to eliminate unwanted symbols and noise, normalization via lemmatization to normalize word forms, and tokenization to split text into useful units appropriate for model input. MDIR-BERT model, being pre-trained on electric power audit texts, efficiently learned domain-specific terms, morphological phenomena, and entity relationships. These preprocessing operations considerably enhanced the textual data quality and uniformity utilized for training and fine-tuning. The model achieved significant accuracy (98.82%), recall, precision, and F1-score improvements, signifying robust performance. It also exhibited very high efficiency through lower energy expenditure, a quicker execution time, and improved convergence rate.

5.1 Limitations and future scopes: In uncertain circumstances, MDIR-BERT gets biased or hallucinatory findings with its performance, which leads to incorrect regulatory decisions. The integrity of an audit could be affected by misuse or a misconception that lacks domain expertise. These limitations show the significance of management and the consistency of power sector control regulations. The quality of domain-specific information is a potential factor that could be further investigated. Additional research intends to develop reasoning capabilities and extend the model's ability to process a broader range of document types. Future research should focus on the generalization of the model to various sectors.

Funding:
This work was supported by Technology Project of State Grid Tianjin Electric Power Company (Grant no. Chengdong Yanfa 2024-05).

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