A Robust Non-Contact Bridge Displacement Tracking Method via KCF-ORB with Scale-Space and Occlusion Handling

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Keywords: bridge engineering; displacement monitoring; KCF; ORB; gaussian pyramid; scale space theory

Received: March 26, 2025

With the growing demand for health monitoring in bridge engineering, non-contact displacement measurement techniques have received extensive attention. A novel bridge displacement monitoring method combining spatially constrained ORB feature extraction with kernel correlation filtering (KCF) and longshort-term tracking learning detection (TLD) algorithms is proposed in the study. The overall method is divided into two stages. First, the traditional ORB feature matching is improved by introducing spatial location constraints to enhance the accuracy of feature point detection and description. Second, the improved features are combined with the KCF tracking framework and a Gaussian pyramid (GP) is introduced to adapt to the scale change. Meanwhile, the TLD algorithm is integrated to deal with the occlusion problem to realize robust displacement tracking. The performance of the proposed method is experimentally validated on the OTB and LaSOT datasets. The results showed that with the optimal parameters (descriptor length of 256 and Gaussian scale number of 4), the feature extraction and tracking accuracy of the new model was close to 0.95, and the detection time was as short as 20ms. The tracking loss rate of the proposed model under 50% occlusion was reduced to 15%. Compared with the state-of-the-art models such as YOLOv5, Mask R-CNN, and Faster R-CNN, the proposed method performed better in terms of precision rate (92.56%), recall rate (90.11%), F1 score (91.10%), and average displacement error (0.01mm). The results show that the proposed method has higher precision, stronger robustness, and better detection efficiency in the complex bridge environment, which provides an effective and reliable technical path for bridge engineering displacement monitoring.

Povzetek: Predlagana je metoda za brezkontaktno zaznavanje pomikov mostov, ki združuje prostorsko omejeni ORB, KCF s prilagoditvijo merila (GP) in TLD za robustno sledenje kljub okluzijam.

1 Introduction

Engineering surveying is an indispensable and important link in fields such as civil engineering, construction engineering, transportation, and energy engineering. Its task is to collect and analyze information on the geometric shape, location, and dimensions of terrain, buildings, structures, and various engineering facilities through scientific and precise measurement methods [1]. Engineering surveying not only provides basic data for the planning and design of projects but also supports positioning, layout, and monitoring after completion during the construction process. In this context, health monitoring and displacement measurement of bridge engineering have gradually become important application areas based on image processing technology. As an important transportation hub, the structural health of bridges is directly related to public safety. Traditional bridge displacement measurement often uses contact sensors such as displacement sensors, accelerometers, etc. However, these methods are affected by complex bridge environments, dynamic loads, and other factors in practical applications, making it difficult to achieve efficient and long-term monitoring [2]. In recent years, non-contact displacement measurement methods based on image processing has received wide attention in bridge health monitoring. Du et al. proposed a new strategy combining template matching and feature point detection for the problem of insufficient accuracy of traditional region-of-interest measurements. This strategy was experimentally verified to have good accuracy and stability in laboratory models, high-speed railroad bridges, and cable-stayed bridges [3]. Colombani and Andrawes improved feature-based image alignment parameters and proposed a new detection method that maintains measurement accuracy within the error range of traditional displacement sensors. The error of this method during laboratory testing was only 3.3% [4]. Han et al. combined adaptive regions of interest with adaptive binarization methods to construct a new detection model to address the issues of interference and large accuracy fluctuations in visual displacement measurement. This model performed well in infrastructure testing at different scales, with high accuracy and feasibility [5]. In addition, to enhance the long-term monitoring effectiveness, Shajihan et al. developed a wireless synchronized SmartVision system, which achieved 94.33% accuracy in the real test of cable-stayed bridges, verifying the

feasibility of wireless visual monitoring [6]. For specific technical applications, kernel correlation filtering (KCF) has become a research hotspot in recent years for its efficient frequency domain target tracking capability [7-8]. Liu et al. combined KCF with log-polar coordinate transformation in ship traveling tracking control, which effectively improved the tracking robustness and accuracy [9]. Oriented-fast and rotated brief (ORB), as a lightweight feature extraction and description algorithm, also shows its potential in bridge monitoring. For example, Bianchi et al. proposed rigid, deformable, and hybrid image alignment strategies based on ORB, which significantly improved the reliability of damage evolution monitoring [10]. Meanwhile, Du et al. designed a visual displacement measurement scheme adapted to different lighting environments by combining ORB with a UAV platform, which verified its efficiency and accuracy in bridge monitoring [11]. Overall, although the existing methods have made some progress in improving the accuracy of non-contact monitoring, there are still problems such as accuracy degradation and unstable tracking in complex environments, especially in coping with target scale changes and occlusion interference. In response to these shortcomings, this article proposes to improve ORB feature extraction by combining spatial constraints with KCF, Gaussian pyramid (GP), and tracking learning detection (TLD) algorithms. This article constructs a robust displacement detection framework for complex engineering scenarios to further enhance the adaptability and reliability of the system. The study gives a comparison summary table of the above different methods, as shown in Table 1.

Table 1: Indicator test results for different models.

Method	Reference	Precision (%)	Recall (%)	F1 Score (%)	Average displacement error (ADE)
Template Matching + Feature Detection	Du et al. [3]	88.75%	85.32 %	86.99%	0.08mm
Feature Image Registration Method	Colombani Andrawes [4]	94.67%	92.43 %	93.54%	0.04mm
Adaptive Region of Interest and Binarization Method	Han et al. [5]	91.20%	89.50 %	90.34%	0.10mm
Wireless Synchronized SmartVision System	Shajihan et al. [6]	94.33%	93.10 %	93.71%	0.05mm
KCF with Logarithmic Polar Coordinate Transformation	Liu et al. [9]	89.35%	87.14 %	88.23%	0.12mm
ORB Combined with Drone	Du et al. [11]	91.88%	90.12 %	90.99%	0.06mm

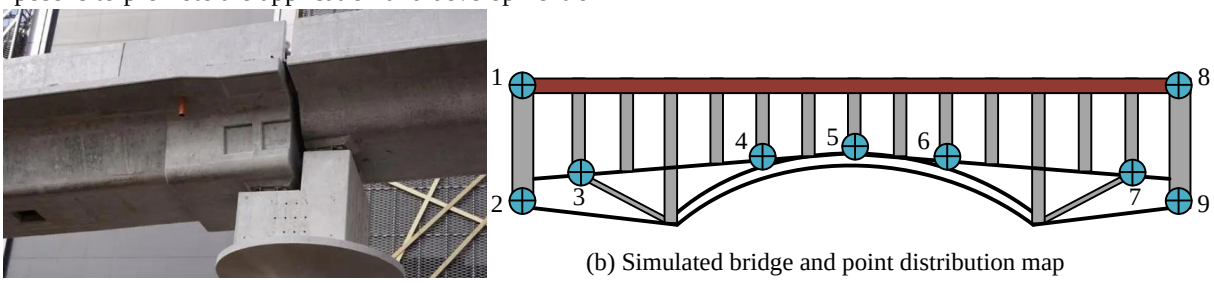
In summary, although there are various computer vision methods applied to bridge displacement detection, there are two major bottlenecks in the existing mainstream technologies. One of them is poor adaptability to changes in target scale. When the camera angle or target distance changes, the detection accuracy is prone to decrease. The second issue is that under partial target occlusion or environmental interference, the tracking robustness is insufficient, which can easily lead to loss or misidentification. These problems seriously limit the practicality and reliability of the visual displacement monitoring system in complex engineering environments. To address the above problems, this paper innovatively proposes a new bridge displacement detection method based on spatial constraints to improve ORB feature extraction, combining KCF with the long short-term TLD algorithm. The overall design is divided into two stages. Firstly, the ORB feature matching process was optimized by introducing a spatial position constraint mechanism, which improved the accuracy and anti-interference ability of feature detection and description. Secondly, the improved features are combined with the KCF framework and combined with GP to enhance the adaptability to scale changes, as well as the introduction of the TLD module to enhance the target recovery ability under occlusion conditions, thereby achieving robust displacement tracking in complex environments. In terms of methodology, this study prioritizes ORB and KCF algorithms that require less computation and are suitable for real-time applications, rather than deep detection methods that rely on large-scale data training. This study is mainly based on literature, indicating that ORB has excellent feature extraction speed and scalability, while KCF is both efficient and stable in small-scale target tracking, with flexible deployment and low cost. It should be noted that the research algorithm outperforms You Only Look Once version 5 (YOLOv5), Mask Region-Based Convolutional Neural Network (Mask R-CNN), and Faster Region-Based CNN (Faster R-CNN) in most of the metrics in the OTB and LaSOT benchmarks. Meanwhile, some of the metrics such as Average Precision (AP) values are close to the other methods in lightly loaded scenarios, so they are not completely superior to other methods in all

comparisons. Focusing on the research motivation, this paper establishes three major objectives. The first is to improve the accuracy and robustness of ORB feature matching through spatial constraint strategies. The second is to integrate KCF with GP and TLD modules to build a robust tracking system adapted to scale change and occlusion environments. The third is to systematically evaluate the performance of the improved model under different loading, occlusion, and scale change conditions. Further specific research questions are proposed, including: how much does the introduction of GP improve the tracking robustness under multi-scale image conditions; The impact of TLD module fusion on detection and restoration under occlusion; The degree of improvement in feature extraction accuracy between spatial constraint matching strategy and standard ORB. Through system modeling, experimental verification, and comparative analysis, the aim is to provide a more accurate, robust, and real-time solution for non-contact displacement monitoring in bridge engineering. The purpose is to promote the application and development of structural health monitoring based on image processing technology in engineering practice.

2 Methods and materials

2.1 Feature extraction and description of engineering images based on improved ORB

Bridge displacement monitoring is a vital component of the bridge health monitoring system. The purpose is to track the displacement of key parts of the bridge in real time, and detect and warn potential structural problems of the bridge promptly [12-13]. This study first simulates the distribution of real bridge structures and their key points. These monitoring points are mainly distributed in areas such as the support structure, mid-span, bridge deck, and connection points of the bridge that are prone to stress concentration and deformation. The simulation diagram is shown in Figure 1.

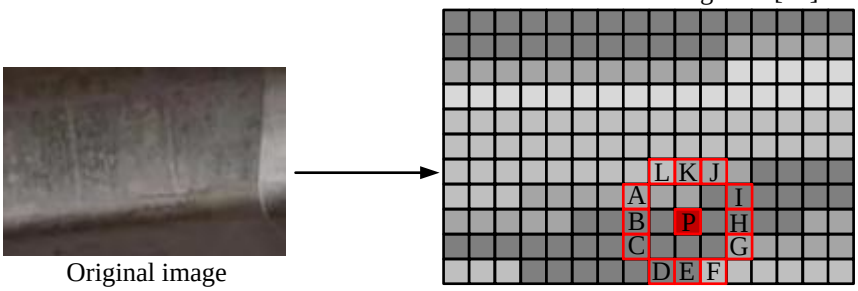


(a) Bridge displacement measurement

(b) Simulated bridge and point distribution map

Figure 1: Schematic diagram of bridge displacement simulation and distribution of monitoring points

Figure 1(a) shows the measured displacement of the bridge under actual stress conditions. The vertical displacement in the mid-span region is more obvious, showing the difference in stress distribution. Figure 1(b) shows the distribution of monitoring points of the simulated bridge. The reasonable distribution of points covers the support structure, the mid-span, and the deck area of the bridge, which can comprehensively reflect the displacement changes of the bridge under different stress conditions. Traditional contact sensors are limited by the environment and use. It is difficult to obtain accurate data for a long time and at a high frequency. This study provides a more efficient and stable solution through video monitoring technology. Traditional contact sensors are limited by environmental conditions and find it difficult to obtain accurate data over a long period of time and at high frequencies. To solve this problem, this study introduces video monitoring technology, which records the displacement changes of bridges under different load conditions through cameras, and combines image processing algorithms to automatically analyze the displacement data. Among them, ORB is a fast and robust feature extraction and matching algorithm. Compared with traditional algorithms, ORB has the advantages of low computational complexity and fast speed, mainly segmented into feature point detection and description [14-15]. Among them, the feature point detection part uses the features from the accelerated segment test (FAST) algorithm to detect corners in the image. Corner detection is shown in Figure 2 [16].



Original image

Angle point detection

Figure 2: Schematic diagram of FAST corner detection process

Figure 2 shows a schematic of the FAST corner point detection process. The working principle of this algorithm is to select a pixel point P in the image, draw a circle around it, and calculate the brightness difference between all pixels on the circle and point P. The algorithm is based on the number of pixel points in the circle. If the number of pixel points within that circle with a larger difference from point P exceeds 0.75 times the circumference of the circle, point P is considered as a key feature point. In this way, FAST corner point detection can effectively identify the significant feature points in an image and provide the basis for subsequent feature matching. The calculation formula for FAST corner detection is shown in equation (1).

$$|I(P)-I(p_i)|>T \quad (1)$$

In equation (1), $I(P)$ is the brightness value of pixel P. $I(P)$ is the brightness value of the i-th pixel on the circumference. T is the preset brightness difference threshold. The corners detected by FAST are further accelerated by ORB using an integral graph to calculate the principal direction of each corner and achieve rotational invariance, as shown in equation (2).

$$\theta=\tan^{-1}\left(\frac{\sum_y (y\cdot I(x,y))}{\sum_x (x\cdot I(x,y))}\right) \quad (2)$$

In equation (2), θ and (x,y) are the main direction and coordinate position of the key point. $I(x,y)$ is the pixel value of the image near the key point. After completing corner detection and main direction assignment, ORB uses the binary robust independent elementary features (BRIEF) algorithm to generate feature descriptors, as shown in equation (3) [17].

$$BRIEF(p_a,p_b)=\begin{cases}1 & if I(p_a)<I(p_b)\\ 0 & otherwise\end{cases} \quad (3)$$

In equation (3), p_a and p_b are the two pixels to be compared. $I(p_a)$ and $I(p_b)$ are the brightness values of pixels p_a and p_b. However, when the distribution of feature points is sparse or the scene is complex, the matching accuracy of the ORB algorithm may be affected. Therefore, this study introduced SCD to improve ORB. The core idea of SCD is to add constraints on spatial position information during the feature point matching process, ensuring that the matched feature points are not only similar in descriptors but also have a certain degree of correlation in spatial position. The improved ORB engineering image feature extraction and description process is shown in Figure 3.

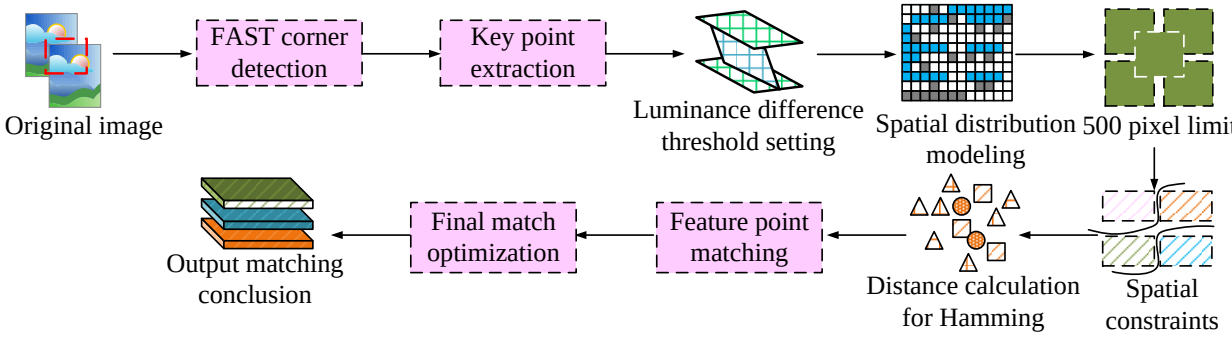


Figure 3: Improved ORB engineering image feature extraction and description process.

In Figure 3, the first step is to use FAST corner detection to extract key points from the image, and set a brightness difference threshold $T=300$ for corner detection. For the detected key points, the second step is to establish a spatial model, record their coordinate positions, and ensure that these points conform to the expected distribution within a 500-pixel range. Feature matching first uses BRIEF to generate feature descriptors, with a descriptor length set to 256 bits. By calculating the Hamming distance of descriptors, preliminary matching pairs are selected, and a matching threshold of 50 bits is set. Then, the spatial position information of the matching points is compared with the expected distribution. Matching points with a spatial distance exceeding 30 pixels will be filtered out to ensure spatial consistency. The spatial distance constraint formula is shown in equation (4).

$$d_s=\sqrt{(x_1-x_2)^2+(y_1-y_2)^2} \quad (4)$$

In equation (4), d_s is the spatial distance between two matching points. (x_1,y_1) and (x_2,y_2) are the coordinates of the matching points in the two images. When the spatial distance d_s is less than the set threshold, such as 30 pixels, it indicates that the matching is effective. The calculation formula for measuring the similarity of feature descriptors using Hamming distance is shown in equation (5).

$$d_h=\sum_{i=1}^{n}(b_1^i\oplus b_2^i) \quad (5)$$

In equation (5), d_h is the Hamming distance between two descriptors. b_1^i and b_2^i are the i-th bits of descriptor 1 and descriptor 2. n is the length of the descriptor.

When the Hamming distance d_h is less than the set threshold, such as 50 bits, the matching is valid.

2.2 Construction of engineering displacement tracking and detection model integrating KCF-ORB

After completing the feature extraction and description of engineering images, this study introduces KCF for target tracking to meet the displacement monitoring requirements in bridge engineering. KCF has significant advantages over other tracking algorithms in fast computation speed and high tracking accuracy. The basic principle is to calculate the response map of the target in the image frequency domain through a correlation filter after initialization, and then find the optimal position of the target [18-20]. The learning formula for the relevant filter is expressed in equation (6).

$$\hat{H} = \frac{\hat{Y} \otimes \hat{X}*}{\hat{X} \otimes \hat{X}* + \lambda} \quad (6)$$

In equation (6), $\hat{H}$ is the frequency domain of the filter. $\hat{X}$ is the frequency domain feature of the target area. $\hat{Y}$ is the ideal output response diagram. λ is the regularization parameter. * is a complex conjugate. The formula for the target response graph is shown in equation (7).

$$R = \eta^{-1}(\hat{H} \oplus \hat{Z}) \quad (7)$$

In equation (7), R is the response graph of the target. η^{-1} is the inverse fast Fourier transform. $\hat{Z}$ is the frequency domain feature of the target area in the current frame. The target update formula is shown in equation (8).

$$\hat{H}_{t+1} = (1-\gamma)\hat{H}_t + \gamma \hat{H}_{new} \quad (8)$$

In equation (8), $\hat{H}_{t+1}$ is the filter for frame $t+1$. γ is the learning rate. $\hat{H}_{new}$ means the novel filter learned in the current frame. The KCF algorithm typically describes the appearance of the target object through ahistogram of oriented gradient (HOG) features. HOG only calculates gradient histograms for local grid images at a single scale, and its computational efficiency is generally poor when the scale is variable. Therefore, this study introduces the theory of scale space. This theory uses GP, which means gradually reducing the image and applying Gaussian smoothing to form multiple levels of image hierarchy, each of which can be used to track the target [21-22]. The GP structure diagram is shown in Figure 4.

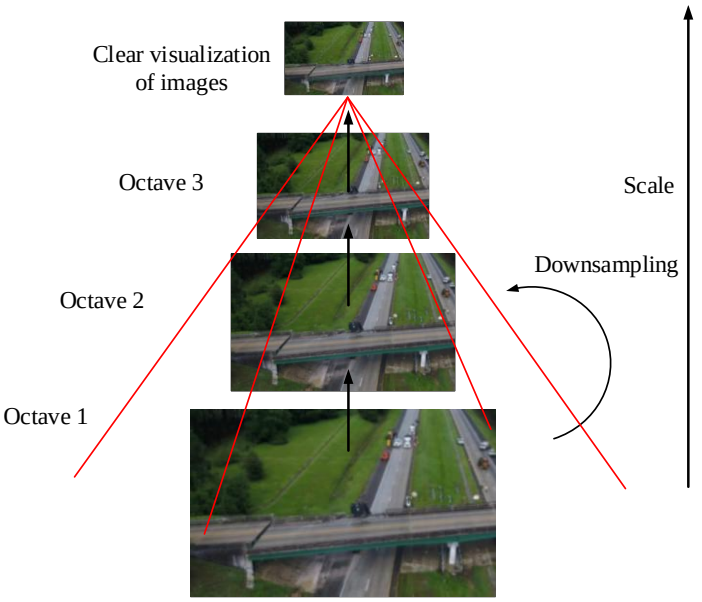


Figure 4: GP principal schematic.

In Figure 4, GP downsamples the original image multiple times to generate hierarchical images of different scales step by step. During the downsampling process, each level of theimage undergoes Gaussian smoothing to remove noise and detail information, ensuring that larger image features remain clear and visible in higher-scale images. Specifically, as the scale increases, the resolution of the image gradually decreases, and the features in the image are also gradually simplified. The GP construction formula is equation (9).

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (9)$$

In equation (9), $L(x, y, \sigma)$ denotes the image in the scale space. $G(x, y, \sigma)$ is a Gaussian kernel. σ is the standard deviation. The calculation formula for downsampling is shown in equation (10).

$$L_{down}(x, y) = L(2x, 2y, \sigma) \quad (10)$$

In equation (10), $L_{down}(x, y)$ is the downsampled image. $L(2x, 2y, \sigma)$ is the image after Gaussian smoothing, and the selected pixel coordinates are sampled every two pixels of the original image. In

addition, to solve the occlusion problem of the KCF algorithm in displacement image feature tracking and detection of bridge engineering, TLD is introduced in this study. Compared to other methods, the learning module in TLD can dynamically update the model based on changes in the appearance of the target during tracking, adapting to changes in features such as shape, brightness, and texture of the target. The KCF-TLD process after combining the two is shown in Figure 5.

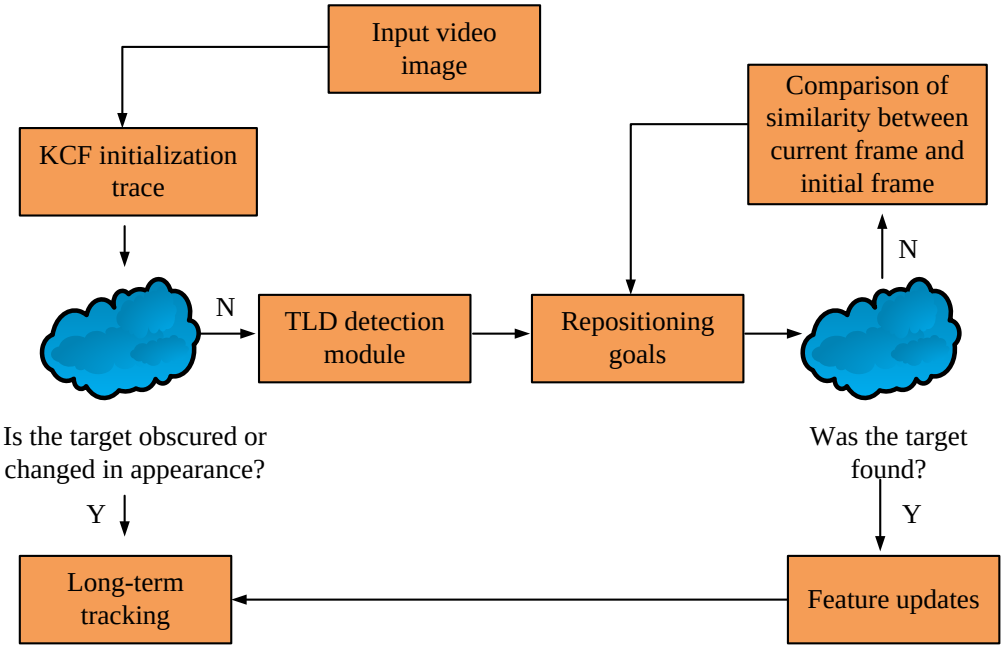


Figure 5: KCF-TLD process.

In Figure 5, step 1 is to conduct a preliminary analysis of the input video and use KCF to initialize and track the target. When there is no obstruction or obvious appearance change of the target, KCF can track the target stably and quickly. However, the KCF algorithm may fail in the presence of target scale changes or partial occlusion. For example, in some test sequences, when the target undergoes rapid motion or is partially occluded, the response value of the KCF may decrease below a threshold, resulting in tracking failure. In this case, the detection module of the TLD is triggered to relocate the target by comparing the similarity with the initial frame. The similarity is usually calculated by cosine similarity or Euclidean distance, and if the similarity is high, the target is considered to be successfully recovered. The key parameters of TLD include the learning rate, the similarity threshold, and the occlusion area threshold. In this study, the learning rate is set to 0.1, the similarity threshold is 0.8, and the occlusion area threshold is 50%.Next, if the TLD detector successfully finds the target, the TLD learning module will learn and update the appearance features of the new target to adapt to subsequent changes in the appearance of the target, ensuring the accuracy of subsequent tracking. Finally, the successfully updated target information will be fed back to KCF for stable target tracking. If the detection fails, the process will end. TLD relocates the target during the detection phase by comparing the similarity between the target in the present and the initial frames. The similarity is calculated as in equation (11).

$$S = \frac{\sum_{i=1}^{n^*}(F_{current}(i)\cdot F_{reference}(i))}{\sqrt{\sum_{i=1}^{n^*}(F_{current}(i))^2}\cdot\sqrt{\sum_{i=1}^{n^*}(F_{reference}(i))^2}} \quad (11)$$

In equation (11), S is the similarity value between the current and reference frames, that is, the initial frame. $F_{current}(i)$ is the feature vector of the target area in the current frame. $F_{reference}(i)$ is the feature vector of the target area in the reference frame. $n*$ is the dimension of the eigenvector. In addition, the expression for updating the objectives of online learning is shown in equation (12).

$$M_{new} = (1-\alpha)M_{old} + \alpha F_{current} \quad (12)$$

In equation (12), M_{new} and M_{old} are the updated and previous frame's target models. α is the learning rate. In summary, this study combines the improved ORB and improved KCF to propose a novel engineering displacement tracking and detection model, as shown in Figure 6.

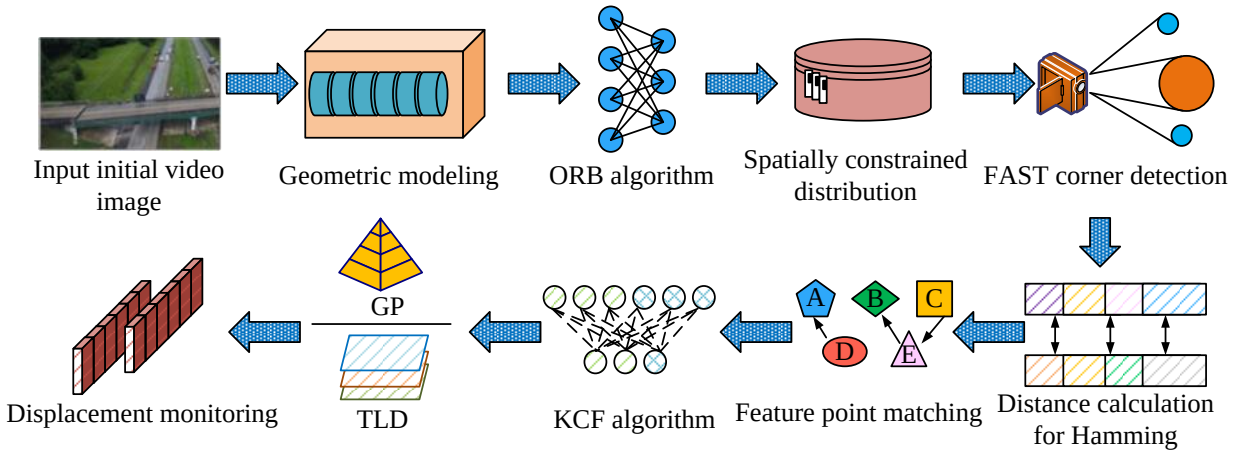


Figure 6: New engineering displacement tracking detection modeling process.

In Figure 6, the processing flow of the new model is mainly separated into 7 steps. Step 1 is to construct a geometric model of the bridge, simulating the stress and deformation of the bridge under actual operating conditions. Step 2 is to identify the key monitoring areas of the bridge, including supporting structures, spans, and bridge decks, to ensure that displacement detection covers critical areas. Step 3 is to use SCD to improve the ORB algorithm, extract key feature points from the image through FAST corner detection, and generate BRIEF descriptors. Step 4 is to calculate the Hamming distance of feature points and introduce spatial position constraints to ensure the accuracy and robustness of feature point matching. Step 5 is to use the KCF algorithm to track the extracted feature points in real time and handle the scale change problem through GP. Step 6, when KCF tracking fails or the target is occluded, the TLD module relocates the target through similarity detection. Step 7, the TLD learning module conducts online learning on changes in the appearance of the target, dynamically updates the target model, and ensures the accuracy of subsequent tracking. The pseudo-code of the algorithm for improving ORB-KCF-GP-TLD is shown in Figure 7.

```
# Step 1: ORB Feature Extraction with Spatial Constraints
def extract_orb_features(image):
    keypoints = detect_keypoints(image)     # Detect keypoints using FAST
    descriptors = compute_orb_descriptors(keypoints)  # Compute ORB descriptors
    constrained_keypoints = apply_spatial_constraint(keypoints)  # Apply spatial constraints
    return constrained_keypoints, descriptors

# Step 2: KCF Tracking
def track_with_kcf(image, target):
    tracker = initialize_kcf_tracker(image, target)  # Initialize KCF tracker
    position = track_target(tracker, image)  # Track the target
    if tracking_failed(position):
        return None  # KCF fails
    return position

# Step 3: TLD for Occlusion Recovery
def recover_with_tld(image, last_position):
    detector = initialize_tld_detector(image, last_position)  # Initialize TLD
    position = detect_target_with_tld(detector, image)  # Detect with TLD
    if position is not None:
        return position
    return None

# Step 4: GP for Scale Adjustment
def adjust_scale_with_gp(image):
    return apply_gaussian_pyramid(image)  # Generate image pyramid for scale change

# Step 5: Combine ORB, KCF, TLD, and GP
def robust_tracking(image, target):
    keypoints, descriptors = extract_orb_features(image)  # Extract ORB features
    kcf_result = track_with_kcf(image, target)  # Track with KCF

    if kcf_result is None:
        tld_result = recover_with_tld(image, target)  # Recover with TLD if KCF fails
        return tld_result if tld_result else None

    # Scale adjustment with GP
    scaled_images = adjust_scale_with_gp(image)
    for img in scaled_images:
        kcf_result = track_with_kcf(img, target)  # Re-track at different scales
        if kcf_result:
            return kcf_result

    return None  # Return None if tracking fails

# Example usage
image = load_image("bridge_frame.jpg")  # Load image
target = define_target(image)  # Define target region

# Run robust tracking
result = robust_tracking(image, target)
if result:
    print("Tracking successful:", result)
else:
    print("Tracking failed.")
```

Figure7: Algorithmic Pseudocode for Improving ORB-KCF-GP-TLD

3 Results

3.1 Performance testing of engineering displacement tracking detection model

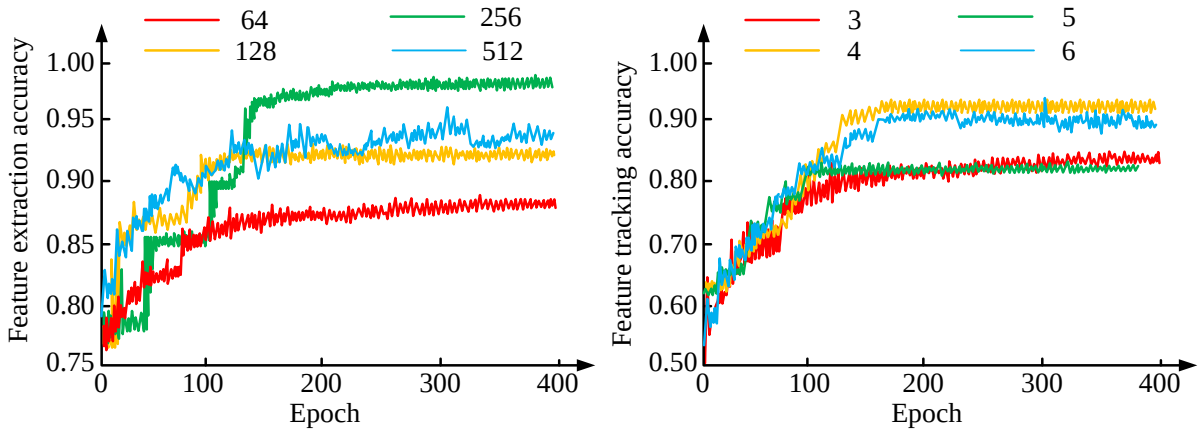
This study sets up a suitable experimental environment, with Intel Core i7-12700K CPU, NVIDIA GeForce RTX 3080 GPU, 32GB DDR4 memory, and Windows 10 64 bit operating system. The Object Tracking Benchmark (OTB) and Large-scale Single Object Tracking Dataset (LaSOT) are used as test data sources. The OTB dataset contains video sequences of 50 different scenarios, and the LaSOT dataset contains 1,400 video sequences covering a wide range of target classes and complex environments. The experimental equipment includes a 20-megapixel Basler ace acA2040-55um industrial camera equipped with a 25-mm lens, a frame rate of 30 fps, and a resolution of 1920×1080. In addition, the bridge model simulated in the experiment adopts standard industrial design. The lighting conditions are natural ambient light and adjustable artificial light sources to ensure experimental accuracy. The programming language used for the model is Python 3.8, and the OpenCV library is used for image processing. The experimental environment and parameters are shown in Table 2.

Table 2: Experimental environment and parameter situation

Parameter Symbol	Algorithm Component	Parameter Description	Setting Value/Explanation
γ (gamma)	KCF	Learning rate used for target update	Default value: 0.2, optimized selection
λ (lambda)	KCF	Regularization parameter controlling filter update smoothness	Default value: 0.01
α (alpha)	KCF	Learning rate for target response, affecting accuracy and stability	Default value: 0.01, optimized value: 0.05
T (threshold)	KCF, ORB	Matching distance threshold for target matching	KCF: 50-bit Hamming distance, ORB: 50-bit (optimized choice)
KCF Kernel	KCF	Type of kernel function used for the correlation filter	Gaussian kernel (Gaussian Kernel)
ORB Pyramid Levels	ORB	Number of pyramid levels for handling scale variation	4 levels (optimal choice based on experiments)
ORB Feature Count	ORB	Maximum number of features to extract	500 features (optimal choice for speed and accuracy)
ORB Descriptor Length	ORB	Length of ORB descriptors, affecting matching accuracy and computation speed	256 bits (optimal choice after experiment)
Gaussian Pyramid σ (sigma)	Gaussian Pyramid (GP)	Standard deviation for Gaussian smoothing in pyramid image generation	Set σ = 1.0 as the standard value
Gaussian Pyramid Levels	Gaussian Pyramid (GP)	Number of levels in the GP	4 levels (providing good scale adaptability in experiments)
ORB Spatial Constraint Range	ORB	Spatial constraint range for feature matching consistency	30 pixels (spatial constraint when matching features)

From Table 2, first, the learning rate γ of the KCF algorithm is set to 0.2, a setting that effectively balances the speed and accuracy of the target update. The regularization parameter λ is 0.01, which aims to ensure smoothness and prevent overfitting during filter updating. The learning rate α of the target response is selected to be 0.01 and optimized to be 0.05 to ensure the accuracy and stability of tracking. The distance threshold T for matching is an important parameter in the KCF and ORB algorithms. For KCF, the threshold is set to 50-bit Hamming distance, and the matching threshold for ORB is also 50-bit, which is optimized through experiments to ensure high efficiency and accuracy of target matching. For the KCF kernel function, Gaussian Kernel is chosen because it has better smoothing, which can reduce the influence of noise in the target tracking process and improve robustness. The pyramid level of the ORB algorithm is set to 4 layers, which makes the algorithm better adapt to changes in the scale of the target and improves the adaptive ability to multi-scale targets. The number of features is set to 500, which is an experimentally verified balance point that ensures speed and accuracy without over-consuming computational resources. The descriptor length of ORB is set to 256 bits, a setting that provides high matching accuracy as well as good computational efficiency. The standard deviation (σ) in the GP is set to 1.0, and the image after Gaussian smoothing can effectively remove the noise and highlight

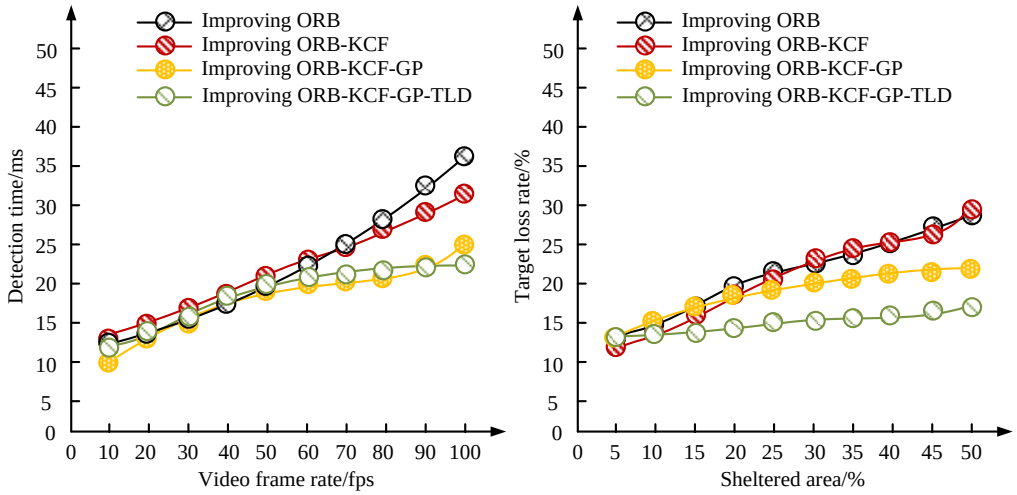
the larger scale features, which helps the algorithm to better deal with scale changes. The number of layers in the GP is set to 4, which is the optimal value chosen based on the experimental results and helps to improve the scale adaptation and image smoothing. The spatial constraint range of the ORB is set to 30 pixels, and this constraint helps to maintain the spatial consistency during the feature matching process, avoiding the mis-matching due to the positional differences. This study first conducts value selection tests on two types of hyperparameters, the BRIEF descriptor length and the GP scale number, to ensure the optimal testing performance of the final model. The result is shown in Figure 8.



(a) BRIEF descriptor length (b) Scale numbers of Gaussian pyramids

Figure 8: Hyperparameter selection test.

Figures 8 (a) and (b) show the test results of selecting values for BRIEF descriptor length and GP degree. In Figure 8 (a), when the descriptor length of BRIEF is 256, the feature extraction accuracy rapidly improves after 100 iterations and maintains high accuracy above 0.95 in subsequent training, demonstrating good stability and convergence. The descriptor with a length of 128 also achieves an accuracy close to 0.90, but its performance is slightly inferior compared to 256. The other two types of BRIEF descriptors perform poorly, especially in terms of 64-bit accuracy and stability. In Figure 8 (b), when the scale of GP is 4, the feature tracking accuracy rapidly improves and stabilizes at around 0.95 in subsequent training, demonstrating the best feature tracking performance. When the scale is 3, 4, and 5, although the accuracy is higher, the overall performance is slightly lower than when the scale is 4. In summary, the optimal length for the BRIEF descriptor is 256, and the optimal number of scales for GP is 4. Under the setting of these two types of hyperparameters, the model achieves optimal performance in feature extraction and tracking accuracy. Figure 9 displays the ablation test results of the final model. Among them, the loss rate is defined as the ratio of the number of frames in which the model fails to successfully identify the target position in the current frame during continuous tracking to the total number of frames. That is, when the intersection integral ratio (IoU) is less than 0.3, the target area is considered a tracking failure area.



(a) Comparison of detection time (b) Masking detection comparison

Figure 9: Ablation test results.

Figure 9(a) shows the results of the ablation test in terms of detection time and Figure 9(b) shows the results in terms of target loss rate. The detection time increases linearly as the video frame rate increases. At 30fps, the detection time of the improved ORB model is 35ms, which decreases to 30ms with the addition of KCF, 25ms with the addition of GP, and 20ms with the combination of TLD, showing the significant effect of the combination of KCF, GP, and TLD in improving the efficiency. In Figure 9(b), the target loss rate increases as the occlusion area increases. Under 20% occlusion, the loss rate of the improved ORB model is 25%, which decreases to 15.4% with the addition of KCF, GP, and TLD. Under 50% occlusion, the loss rate of the improved ORB is %, while the loss rate of the combination of TLD is 15.0%. These results show that TLD effectively reduces target loss in the occlusion case. Spatial constraint distribution (SCD) significantly improves the stability of feature matching, especially under occlusion and motion blur conditions. SCD reduces mis-matching and enhances robustness by ensuring the spatial consistency of the matched features.KCF performs excellently in tracking accuracy and real-time performance. GP enhances the adaptability of the system to targets of different scales. The TLD module effectively solves the occlusion problem. The three together improve the stability and accuracy of the model in complex environments. In addition, the paper utilizes precision (P), recall (R), F1 score, and average displacement error (ADE) as indicators to introduce a more cash-based algorithm model for comparison. For example, YOLOv5, Mask R-CNN, and Faster R-CNN are tested. Table 3 lists the specific results. Among them, the parameters of YOLOv5 are set, withan input size of 640×640, batch size of 16, learning rate of 0.001, using default pre-training weights. Mask R-CNN uses ResNet50 backbone, with an input size of 800×800, batch size of 16, learning rate of 0.0025, using COCO pre-training weights. Faster R-CNN uses ResNet50 backbone, withan input size of 800×800, batch size of 16, learning rate of 0.0025, using ImageNet pre-training weights. CNN uses a ResNet50 backbone with an input size of 600×600, batch size of 8, learning rate of 0.001, using ImageNet pre-training weights. The parameters of all baseline methods are kept in the same training conditions to ensure a fair comparison.

Table 3: Indicator test results for different models.

Data set	Model	P/%	R/%	F1/%	ADE/mm	*p*
OTB	YOLOv5	87.91	88.71	88.31	0.02	0.003
	Mask R-CNN	89.84	86.52	88.18	0.02	0.006
	Faster R-CNN	90.17	88.45	89.31	0.03	0.012
	Research model	92.56	89.29	90.93	0.01	/
LaSOT	YOLOv5	88.24	85.27	86.76	0.02	0.004
	Mask R-CNN	90.63	86.58	88.61	0.02	0.009
	Faster R-CNN	90.89	88.72	89.81	0.02	0.015
	Research model	92.08	90.11	91.10	0.02	/

As shown in Table 3, the proposed model demonstrates superior performance on both OTB and LaSOT datasets. On the OTB dataset, the accuracy of the proposed model is 92.56%, the recall is 89.29%, the F1 score reaches 90.93%, and the ADE is only 0.01 mm. On the LaSOT dataset, the P value is 92.08%, the R value is 90.11%, and the F1 score is 91.10%. Compared with the state-of-the-art methods such as YOLOv5, Mask R-CNN, and Faster R-CNN, the present model shows significant advantages in the two key indexes, namely, F1 score and ADE. It is further verified by t-test that there are statistically significant differences in multiple performance metrics at the $p<0.01$ level, indicating that the present model possesses stronger displacement tracking accuracy and robustness in complex environments.

3.2 Simulation testing of engineering displacement tracking detection model

In this study, the experimental simulation is conducted using a 20-megapixel industrial camera equipped with a 25mm lens, model Basler ace acA2040-55um, with a frame rate of 30fps and a resolution of 1920×1080.This camera is used to simulate the displacement variations of the bridge structure under different stress conditions. The simulation environment is built based on the Unity 3D engine and simulates various forces and environmental conditions of the bridge, including light load, medium load, and heavy load. The experimental simulation scenario is exhibited in Figure 10. Light, middle, and heavy loads represent different bridge stresses. Light and small loads simulate the stress of bridges under normal traffic flow. Middle load refers to simulating the stress of a bridge under high traffic flow or when light vehicles pass through it with a medium load. Heavy load represents simulating the stress of bridges under heavy vehicles or extreme weather conditions using large loads.



Figure10: Experimental simulation scenarios.

Based on this environment, this study conducts tests using AP and actual monitoring time as indicators. Figure 11 shows the detection comparison of four models.

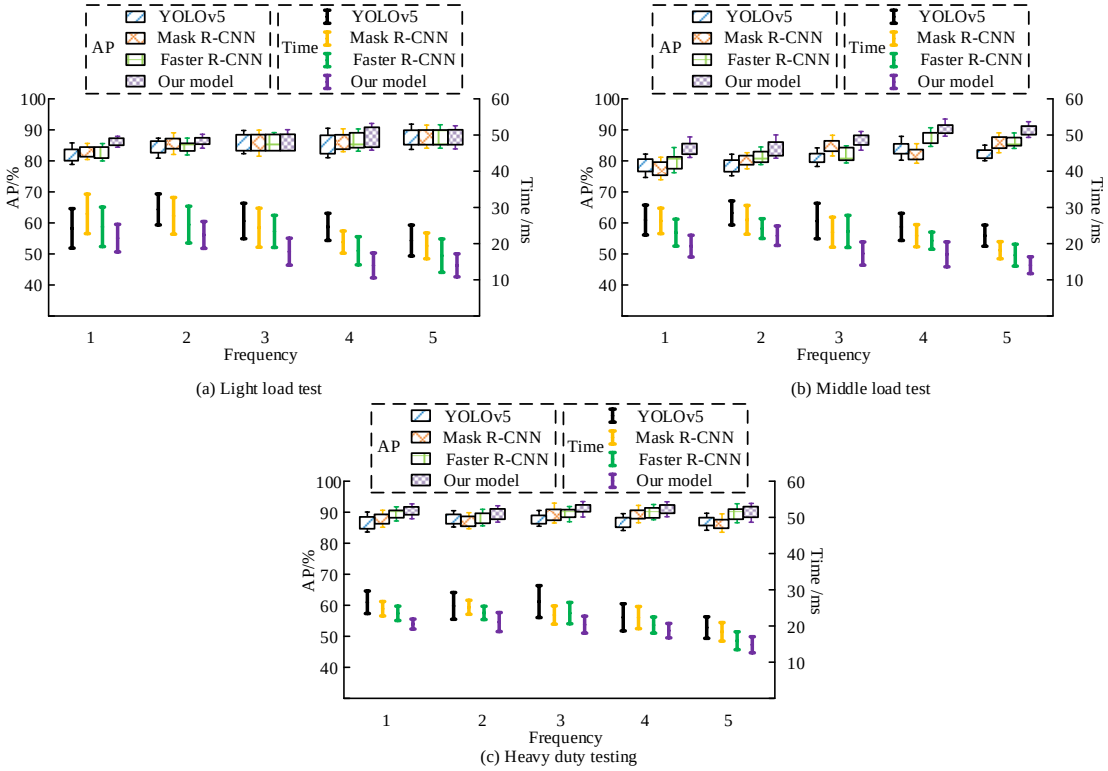


Figure 11: Displacement monitoring tests under different loads.

Figures 11 (a), (b), and (c) show the test results of model indicators under light, middle, and heavy loads. In Figure 11, under light load conditions, the AP values of YOLOv5, Mask R-CNN, and Faster R-CNN are 88.21%, 89.34%, and 89.91%, respectively. The research model reaches 92.17%, which is about 2.5% higher than the average, while the detection time is 15ms, which is about 40% faster than the average time of other models. Under middle load conditions, the AP values of YOLOv5 and Mask R-CNN are 85.38% and 86.72%, respectively, while the AP value of Faster R-CNN is 90.03%. The AP value of the research model is 92.06%, leading by about 1.5% to 6.5% respectively. The detection time is 30ms, which is nearly 25% faster than the average of the other three. Under heavy load environment, the APs of YOLOv5 and Mask R-CNN are 83.41% and 85.14% respectively, and 88.06% for Faster R-CNN. The research model still reaches 91.33%, with a lead of up to 7.9%, and the detection time is controlled at 40ms, which is much lower than the other models with a processing delay of about 55ms. Overall, the research model maintains high detection accuracy and fast operational efficiency under all three load conditions. Especially with the increase of load, its accuracy advantage becomes more significant, indicating that this method has stronger robustness and engineering adaptability to complex stress scenarios. This study tests displacement and absolute error (AE) as indicators, as listed in Table 4.

Table 4: Displacement and absolute error testing.

Conditional	Model	True displacement value/mm	Monitoring of displacement values/mm	AE/mm	*p*
Light load	YOLOv5	3.91	3.14	0.37	0.007
	Mask R-CNN	3.91	3.43	0.26	0.021
	Faster R-CNN	3.91	3.77	0.18	0.063
	Research model	o	3.89	0.07	0.000
Middle load	YOLOv5	9.24	9.01	0.28	0.009
	Mask R-CNN	9.24	9.12	0.16	0.025
	Faster R-CNN	9.24	9.33	0.15	0.039
	Research model	9.24	9.18	0.09	0.002
Heavy load	YOLOv5	18.87	18.21	0.44	0.006
	Mask R-CNN	18.87	18.64	0.28	0.014
	Faster R-CNN	18.87	18.57	0.31	0.018
	Research model	18.87	18.81	0.11	0.001

From Table 4, under light loading conditions, the monitored displacement values of the research model are closest to the real values, with an AE of 0.07 mm, p=0.000, which is significantly better than the other models, and the YOLOv5 error is the largest of 0.37 mm. Under middle loading conditions, the AE of the research model is 0.09 mm, p=0.002, which is lower than that of Mask R-CNN (0.16 mm, p=0.025) and Faster R-CNN (0.15 mm, p=0.039), and the error of YOLOv5 is still high at 0.28 mm. Under heavy loading, the AE of the research model is 0.11 mm (p=0.001), which still has a higher error than that of YOLOv5 (0.44 mm), Mask R-CNN (0.28 mm), and Faster R-CNN (0.31 mm). This indicates that its displacement measurement accuracy and consistency under multi-load conditions are better than the comparison models. Under the same loading conditions and shooting angles, the deviation of the simulation data from the measured data in terms of the number of features extracted at key points is less than 4%, and the ADE is controlled within 0.15 mm. This indicates that the constructed simulation environment has good engineering realism, and it can be an effective alternative to some of the real test scenarios for the verification of the algorithm. Overall, the research model has the highest displacement monitoring accuracy and the smallest AE under different loads, indicating that it has stronger displacement detection capability and robustness.

4 Discussion

The proposed displacement detection model based on spatial constrained ORB feature matching combined with KCF-GP-TLD exhibits performance advantages over existing mainstream methods in multiple indicators, mainly due to the introduction of three key improvements. First, the spatial constrained strategy effectively enhances the accuracy and noise resistance of ORB feature point matching, especially in the presence of motion blur or complex background texture, significantly reducing the false matching rate. Second, the GP structure improves the stability of KCF under target scale changes, ensuring that high tracking accuracy can still be maintained under different camera distances, viewpoints, or target scaling. Third, the fusion of the TLD module improves the recovery ability of the model in occluded scenes, and the loss rate is still lower than 20% when the occluded area reaches 50% in the experiments, which is significantly better than that of the model without the introduction of TLD. In the comparison with advanced models such as YOLOv5, Mask R-CNN, and Faster R-CNN, the research model has more than 2% advantages in AP value and F1 score on both OTB and LaSOT datasets. ADE has been reduced by approximately 0.01-0.02 mm, and the fastest detection time can reach 20 ms, achieving a better balance between accuracy, real-time performance, and robustness. This performance improvement does not come from deep learning training, but relies on the optimized combination among lightweight algorithms, which is particularly suitable for real-time engineering monitoring scenarios. In addition, the model performs particularly well in simulating heavy loads and obstructed environments, maintaining high accuracy and low error even under high-stress or low-visibility conditions. This indicates its applicability and low engineering

deployment cost, particularly suitable for embedded monitoring systems in small and medium-sized bridge sites.

However, this study did not introduce real video data from real bridge engineering. At present, the experimental evidence mainly comes from the OTB and LaSOT standard datasets, as well as the comprehensive simulation platform built on Unity 3D, which cannot fully cover the effects of real problems such as sensor noise, lighting changes, and viewpoint occlusion. Therefore, future research should be further extended to practical engineering scenarios, and cross-environment generalization validation should be performed in combination with real surveillance devices to further verify the practicality and scalability of the method.

5 Conclusion

In response to the shortcomings of traditional displacement measurement techniques in complex environments in bridge engineering, this study introduced the ORB feature matching technology of SCD and combines GP and TLD with KCF to optimize feature point detection and tracking. A new non-contact displacement monitoring method has been proposed. The experiments showed that the feature extraction accuracy and feature tracking accuracy of the model could reach about 0.95 in the OBR dataset with the settings of BRIEF descriptor length of 256 and the number of GP layers of 4. The ablation experiment further validated the performance improvement of the sub-module. The complete model that integrated KCF, GP, and TLD had the best performance under occlusion and scale change conditions, with a detection time of the shortest 20 ms and an average target loss rate of 15%. In the OTB and LaSOT datasets, the model had the highest detection precision of 92.56%, the highest recall of 90.11%, the highest F1score of 91.10%, and the lowest ADE of 0.01 mm, which is better than the mainstream models such as YOLOv5, Mask R-CNN, and Faster R-CNN.This indicated that the new model had higher tracking accuracy and smaller displacement detection errors in complex scenarios. Simulation tests have found that the monitoring AP value and monitoring time of the research model are significantly better under light, middle, and heavy load environments. Especially under heavy load conditions, the average error was only 0.11mm, which was better than traditional algorithms such as YOLOv5 and Faster R-CNN. Although the research model has significantly improved in performance, there are still some robustness issues when dealing with extreme lighting changes and prolonged monitoring. Future research will continue to optimize the model's light adaptability and further integrate more intelligent detection algorithms to improve the system's performance in complex dynamic environments.

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A Probabilistic Neural Network-Based Dynamic Perception Framework for Rehabilitation Robots Using Multi-Modal Sensor Fusion

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Keywords: multi-modal, sensors, information fusion, robot, dynamic perception

Received: March 24, 2025

The current mechanical dynamic perception methods for rehabilitation-assisted robots have low accuracy and low efficiency. In response to this problem, a robot mechanical dynamic perception model based on multi-modal sensor fusion is proposed in the research. The interaction force sensor and weight sensor are used to collect the interaction force and weight loss values during the patients' motion process, with a sample size of 5,378 collected. Then, the Kalman filtering algorithm is used for data processing. Finally, the sensor information is fused using a weighted fusion method, and a probabilistic neural network is used to determine the patient's motion, thereby achieving intelligent dynamic perception in rehabilitation training. The probabilistic neural network architecture includes the input layer, the hidden layer, and the output layer. The experiment was simulated and analyzed using MATLAB, and five volunteers were selected to carry out practical experiments. The results showed that the mechanical dynamic perception model proposed in the study could accurately perceive the motion intention of the user through multi-modal sensors and make accurate judgments. Its judgment accuracy reached 95.52%, and the response time was only 0.85 seconds. Compared with traditional rehabilitation assisted robot mechanical dynamic perception methods, this model significantly improves accuracy and efficiency. The method proposed in the study can further enhance the dynamic perception ability of robots through multi-modal sensor fusion, thereby improving the intelligence of rehabilitation training.

Povzetek: Predlagan je model dinamične zaznave rehabilitacijskega robota, ki s fuzijo interakcijskih in težnostnih senzorjev ter probabilističnim nevronskim omrežjem izboljša natančnost prepoznavanja pacientovega gibanja.

1 Introduction

The key technology for robots to achieve intelligent operation and motion control involves comprehensive perception of the environment and their own state, providing accurate information support for robot decision-making [1]. Driven by intelligent technology, the application of sensor technology in the field of robotics is becoming increasingly widespread. However, the information acquisition of a single sensor often has limitations and cannot meet the perception needs in complex environments. Therefore, multi-modal sensor fusion technology has emerged. The information from different sensors is integrated to improve the robot's perception accuracy of the external environment [2]. Challa et al. found that the stability of bipedal robots during walking was difficult to maintain. Therefore, a gait trajectory generation method based on long short-term memory networks was built. This method adopted motion capture sensors to capture gait data of humans walking on a treadmill. Finally, the sensor data was applied to the gait trajectory generation model. This method could effectively reduce the swinging of bipedal robots during walking and improve walking stability [3]. Zan proposed a path planning method based on whale optimization algorithm and computer perception to improve the path planning performance of robots in complex environments. This method achieved path obstacle avoidance through visual sensors. The path efficiency and smoothness planned by this method were significantly improved [4]. Shi et al. combined ultrasonic sensors and flexible frictional electric sensors to assist robots in perceiving objects to improve their ability to recognize and judge captured objects. The method achieved a recognition accuracy of 92.48% for captured objects [5].

At present, robots with high requirements for mechanical dynamic perception are mainly used in high-precision manufacturing, medical surgery, aerospace, and other fields. In these applications, robots need to be able to perceive and operate accurately to complete tasks [6-8]. Rajendran et al. reviewed the current research challenges of the selective harvesting robot to enhance the dynamic perception capability. The improvement

effect of integrating artificial intelligence, soft robots, and data-driven methods on the perception ability was discussed. The results indicated that data-driven methods and integrated artificial intelligence could significantly enhance the dynamic perception ability of robots, especially when dealing with complex and changing environments [9]. Wang et al. found that currently most soft actuators only had a single driving element and lacked perception. A dielectric elastomer actuator with multi-degree of freedom driving and perception functions was proposed to address this issue. By stimulating the selective dynamic of electrodes, all-round braking and perception were achieved. After applying this method, the robot's grasping action was more flexible [10]. Chen et al. designed a multi-modal fusion method based on deep learning to explore the collaborative intention recognition of robots towards human colleagues. This method combined visual, auditory, and tactile sensors to predict the behavior and intention through deep learning models. This method had high accuracy in human colleague collaboration intention recognition and could effectively improve the collaboration efficiency between robots and human colleagues [11]. Yan et al. proposed a robot with dynamic perception to assist surgeons in surgical procedures. The robot system predicted and perceived the insertion status of the guide wire through force feedback perception. The robot system assisted physicians in judging surgical progress and making intelligent decisions based on prediction and perception results. The perception accuracy reached 93.62% [12]. The comparison and summary of the performance indicators of the existing related work are shown in Table 1.

Table 1: Comparison and summary of the existing related work

Document Number	Title of Literature	Response time (s)	Perception accuracy (%)
[3]	An optimized-LSTM and RGB-D sensor-based human gait trajectory generator for bipedal robot walking	0.73	85.46
[4]	Research on robot path perception and optimization technology based on whale optimization algorithm	0.68	89.77
[5]	Soft robotic perception system with ultrasonic auto-positioning and multimodal sensory intelligence	0.71	90.12
[6]	Tacto: A fast, flexible, and open-source simulator for high-resolution vision-based tactile sensors	0.65	90.35
[9]	Towards autonomous selective harvesting: A review of robot perception, robot design, motion planning and control	0.66	90.74
[10]	Electroactive polymer-based soft actuator with integrated functions of multi-degree-of-freedom motion and perception	0.69	87.11
[11]	Influence of mobile robots on human safety perception and system productivity in wholesale and retail trade environments: A pilot study	0.70	90.23
[12]	Machine learning-based surgical state perception and collaborative control for a vascular interventional robot	0.77	89.56

As shown in Table 1, the current mechanical dynamic perception model still has problems such as low accuracy and poor real-time performance in perceiving the operator's motion intention in the process of assisting rehabilitation medical treatment [13]. Existing perception models have problems such as single sensor mode, insufficient multi-modal fusion, and low efficiency in PNN applications, which limit their perception accuracy and real-time performance in complex environments, making it difficult to meet the requirements of efficient collaboration and precise operation. This is because the sensor data fusion algorithm is not optimized enough, fails to make full use of multi-source information, and the PNN has low computational efficiency when processing large-scale data, resulting in the response speed and accuracy of the model in a dynamic environment being difficult to meet the clinical application standards. Therefore, multi-modal sensing information is combined to further enhance the dynamic perception capability of machinery. A robot mechanical dynamic perception model based on multi-modal sensors is proposed. This model analyzes the gait of patients and uses multiple sensors to identify and judge the intentions, further achieving the intelligence of rehabilitation training. The innovation of the research lies in taking the interaction force sensor and the weight sensor as the main features in the dynamic perception process of the robot. The accuracy of dynamic perception is further improved through the feature fusion of multi-modal sensors. Furthermore, the research proposed a mechanical motion pattern judgment model based on probabilistic neural networks, further enhancing machine's power sensing capability and assisting it in determining the appropriate next action. The research aims to improve the response speed and accuracy of the model in complex environments through multi-modal fusion and probabilistic neural network optimization, meet the requirements of clinical applications, and ultimately achieve efficient and precise rehabilitation training assistance. This is to address the bottleneck of perception accuracy and real-time performance caused by insufficient fusion of single perception mode and multiple modalities in current research, ensuring that the model

can quickly and accurately identify the patient's intention in a dynamic environment, and improving the effectiveness and safety of rehabilitation training.

2 Methods and materials

To assist users in motion, a robot mechanical dynamic perception model based on multi-modal sensor fusion is proposed. This model combines interaction force sensors and weight sensors to perceive the patient's motion intention, thereby assisting users in exercise training.

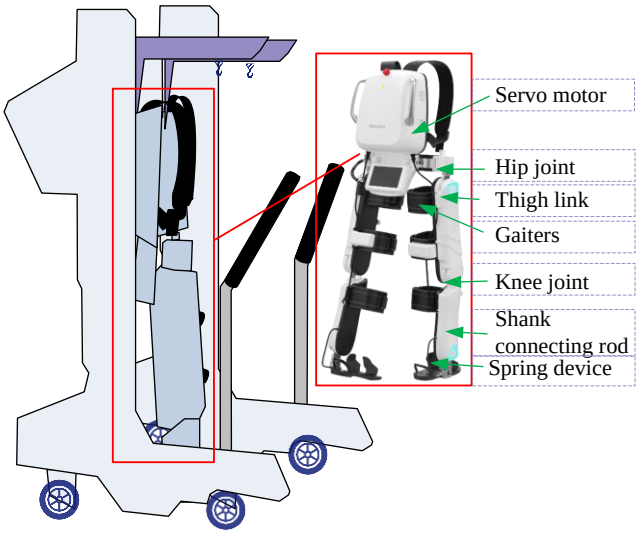
2.1 Perception data acquisition and signal processing based on multi-modal sensor fusion

Conventional image perception acquisition methods generally suffer from low acquisition accuracy. Therefore, the study first takes a gait analyzer to accurately divide the support phase and swing phase during walking [14-15]. In addition, interaction force sensors are used to obtain human-machine interaction force to evaluate the dynamic state of robot users during motion. To obtain more accurate dynamic perception data, the weight sensor is combined to further analyze the gait characteristics of users by monitoring the changes in their lower limb weight-bearing capacity. The placement position, sensor accuracy, sampling rate, and data range of each sensor are shown in Table 2.

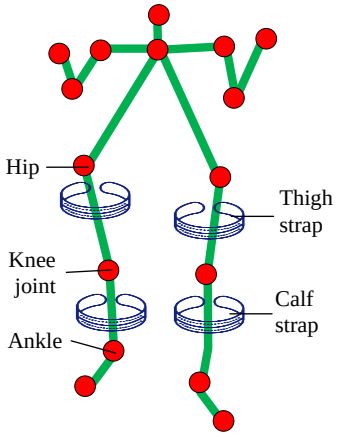
Table 2: Details of sensor placement

Serial number	Placement position	Type	Accuracy	Sampling rate (Hz)	Data range
1	Servo motor	Interaction force sensor	±0.5N	100	The full cycle of walking
2	Hip joint		±0.5N	100	The full cycle of walking
3	Thigh link		±0.5N	100	The full cycle of walking
4	Gaiters		±0.5N	100	The full cycle of walking
5	Knee joint		±0.5N	100	The full cycle of walking
6	Shank connecting rod		±0.5N	100	The full cycle of walking
7	Spring device		±0.5N	100	The full cycle of walking
8~9	At the left and right pull rods	Weight sensor	±0.1kg	50	The full cycle of walking

The dynamic perception robot proposed in the study and the fixed method acting on the patient's motion stage are shown in Figure 1.



(a) Lower limb rehabilitation robot structure



(b) The fixed pattern of the rehabilitation training phase

Figure 1: The proposed dynamic perception robot and the fixed mode acting on the patient's motion stage.

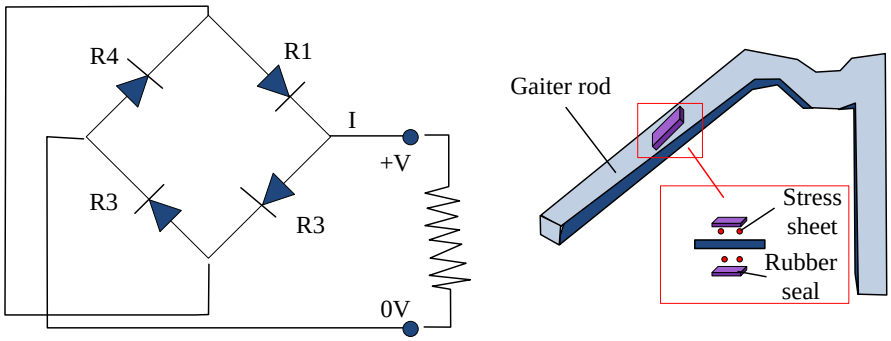
In Figure 1 (a), the robot in the study has an adjustable fixing device for adjusting between users of different heights and body types. Multiple sensor interfaces are also equipped in the structure to connect gait analyzers, interaction force sensors, and weight sensors, ensuring accurate data collection and transmission. In Figure 1 (b), the robot is bound to the user through leg warmers and straps. The interaction torque between the lower limbs and the machine is transmitted to the user's legs through the leg warmers. Therefore, the leg warmer is taken to design interaction force sensors that extract the interaction force during the motion. The dynamic equation of the motion perception robot is shown in equation (1).

$$\gamma = M(\alpha)\alpha'' + C(\alpha,\alpha')\alpha' + g(\alpha) - \psi \tag{1}$$

In equation (1), α, α', and α'' represent the swing angle of the rehabilitation robot and its first and second derivatives. $C(\alpha,\alpha')$ is the acceleration of the robotic arm. $g(\theta)$ is the gravity matrix. $M(\alpha)$ is the Coriolis acceleration matrix. γ is the joint torque of the rehabilitation robot arm. ψ is the interaction force between humans and machines. The interaction force between humans and machines is shown in equation (2).

$$\psi = \begin{bmatrix} S_3\cos\varepsilon & 0 \\ -S_3\cos\varepsilon & 0 \end{bmatrix}^T \phi\Delta x_3 + \begin{bmatrix} L_3\cos\varepsilon + S_4\cos(\eta+\varepsilon) & S_4\cos(\eta+\varepsilon) \\ -L_3\cos\varepsilon - S_4\cos(\eta+\varepsilon) & -S_4\cos(\eta+\varepsilon) \end{bmatrix}^T \phi\Delta x_4 \tag{2}$$

In equation (2), S_3 represents the distance from the patient's hip joint to the thigh binding rod. L_3 represents the length of the thigh and the thigh connecting rod. S_4 represents the distance from the knee joint to the calf connecting rod. ε represents the angle between the hip joint of the leg and the hip joint of the machine relative to the vertical line of the ground. η represents the angle between the knee joint of the human and the machine relative to the thigh connecting rod. φ represents the stiffness coefficient of the binding rod. It is set as a constant value in the research. The value is 1,000 N/m. Δx_3 and Δx_4 are respectively the displacements of the centroids of the thigh connecting rod and the calf connecting rod. Based on the interaction force calculation method and interaction force sensor data, the current motion status of rehabilitation training is perceived. Due to the high accuracy, wide measurement range, and long lifespan of resistance strain gauges, they are chosen for research to achieve interaction force perception. The circuit and installation location of the resistance strain gauge used in the study are shown in Figure 2.



(a) Strain gauge full bridge circuit (b) Stress sensor layout

Figure 2: Circuit of resistance strain gauge and installation position.

As shown in Figure 2 (a), a full bridge circuit is taken to connect resistance strain gauges to improve measurement accuracy and stability. This circuit can eliminate the influence of environmental factors such as temperature and ensure the accuracy of interaction force data. As shown in Figure 2 (b), four strain gauges are placed on each leg rod. These strain gauges can sense the slight deformation of the leg rod under force and convert it into a change in resistance value. During the user's motion, there are interactions with the machine, causing deformation of the strain gauge and resulting in a change in its resistance value. By measuring the changes in these resistance values, the interaction force between the user and the machine can be indirectly obtained. The specific process of resistance change is shown in equation (3).

$$K = \frac{\Delta R}{R} \tag{3}$$

In equation (3), R signifies the original resistance, measured in Ω. ΔR is the change in resistance, measured in Ω. K is the sensitivity coefficient of the resistance strain gauge, which is dimensionless. In addition to interaction force perception, the weight sensor is taken to detect changes in the user's body center of gravity and lower limb weight-bearing capacity. The weight perception proposed in the study is achieved through tension sensors arranged at different positions. The screw sensor is used to measure weight loss data during walking. After wearing the weight loss suit, the user connects the weight loss rope on the suit to the simple tension sensor on the weight reducing arm. By measuring the tension of the weight loss rope during the patient's walking process through a tension sensor, the weight-bearing capacity of the affected limb can be indirectly obtained. To avoid interference signals during the perception process, the Kalman filtering algorithm is used to preprocess sensor signals. The structure of the Kalman filter is shown in Figure 3.

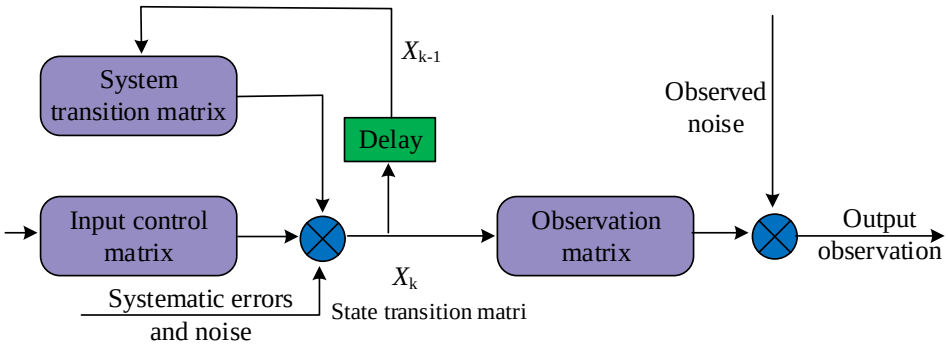


Figure 3: Kalman filter structure.

In Figure 3, the Kalman filter algorithm can effectively remove noise and interference, improve signal accuracy and reliability through prediction and update. In the prediction stage, the algorithm estimates the current state based on the state of the previous moment. In the update phase, the algorithm combines the current observation values to correct the prediction results and obtain the optimal state estimation. Based on this approach, the study ensures the stability and accuracy of sensor signals, providing a reliable data foundation for subsequent power perception models.

2.2 Mechanical dynamic perception model based on probabilistic neural network and multi-modal sensors

After setting up sensors and introducing filtering algorithms to process sensor signals, the probabilistic neural network is introduced to achieve mechanical

dynamic perception of robots. Through dynamic perception, robots assist users in motion. The user's motion mode includes two types: active and passive, which are classified according to the user's autonomous walking ability [16]. To enhance the applicability of the proposed robot, the information obtained from multi-modal sensors is utilized to achieve mechanical dynamic perception, and uses probabilistic neural networks to determine the user's motion pattern. The data during the training process is collected in real time through multi-modal sensors, including parameters such as force, displacement, and velocity. After preprocessing, it is input into the probabilistic neural network. The dataset is divided into the training set and the test set with a ratio of 7:3. The training process is subjected to ten-fold cross-validation to ensure the generalization ability of the model. The study takes high-performance computers for model training, equipped with Intel i9 processors, 64GB of memory, and NVIDIA RTX 3080 graphics cards. The operating system is Windows 11, the programming environment is Python 3.9, and the main dependency libraries include TensorFlow and Scikit learn. The sensor calibration program uses standard weights for static calibration to ensure measurement accuracy. The model parameters are optimized through grid search, and the final number of hidden layer nodes is determined to be 20 with a learning rate of 0.01. During the training process, the changes in the loss function are monitored in real-time to avoid over-fitting. To fuse multi-modal perception information, the weighted summation method is taken to integrate the feature information from different sensors. The specific process of the sensor data fusion method used in the study is shown in Figure 4.

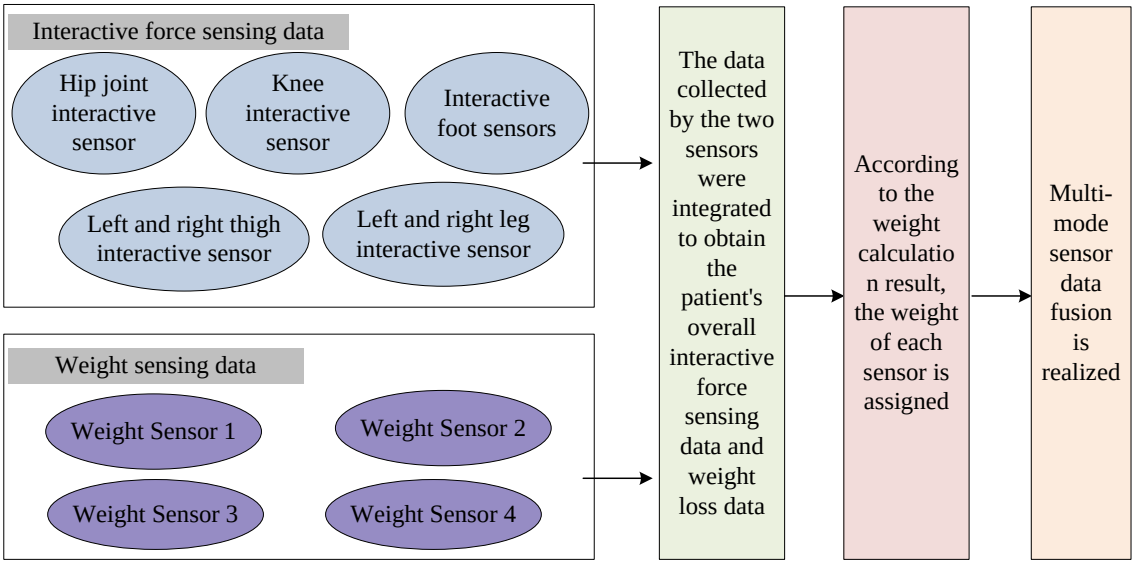


Figure 4: The specific process of sensor data fusion method.

In Figure 4, firstly, the data collected by multiple sensors is pieced together to obtain the overall motion data of the patient. Then, the weight assignment is performed based on the weight values of each sensor to further achieve feature fusion. The weight calculation method for sensors is shown in equation (4).

$$w_i = \left[\sigma_i^2 \sum_{i=1}^{n} \frac{1}{\sigma_i^2} \right]^{-1} \tag{4}$$

In equation (4), σ_i is the measurement variance of the sensor. i is the sensor serial number. n is the number of sensors. w_i signifies the weight of the corresponding sensor. The measurement variance of the sensor is calculated based on multiple experimental data during the training process. The benchmark data adopted in the study is the kinematic model established by healthy subjects performing standard motions, which serves as a reference standard for auxiliary rehabilitation training. After obtaining the corresponding interaction force and weight loss value generated by the user during the gait cycle through data fusion, the probabilistic neural network is used to judge their motion patterns and further enhance the intelligence. Probabilistic neural network is a radial basis function network, which includes an input layer, a pattern layer, a summation layer, and an output layer [17]. Figure 5 displays the structure of the probabilistic neural network.

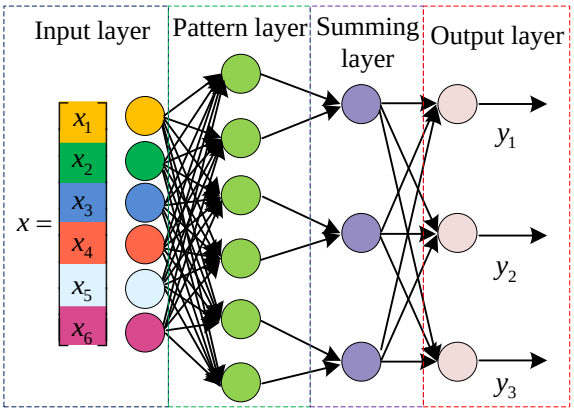


Figure 5: The structure of probabilistic neural network.

In Figure 5, in the probabilistic neural network, the input layer is responsible for receiving fused data from sensors. The pattern layer calculates the similarity between the input data and each training sample. The summation layer weights and sums the similarity to obtain probability estimates for each category. The output layer determines the final classification result based on the probability estimate. When using the probabilistic neural network for classification, the losses and risks in practical applications are considered. Probabilistic neural networks are sensitive to smoothing factors and data distribution, and need to be finely adjusted to optimize the classification effect. Therefore, the grid search method is taken to determine its smoothing parameters. The research conducts grid search, traverses different combinations of smooth parameters, evaluates the classification accuracy, and finally selects the optimal parameters. The input-output relationship determined in the hidden layer is shown in equation (5).

$$\xi_{kj}(x) = e^{\frac{(x-x_{kj})(x-x_{kj})^T}{\sigma^2}} \cdot \left[\sqrt{2\pi}\sigma^d\right]^{-1} \tag{5}$$

In equation (5), $\xi_{ij}(x)$ is the output of the hidden layer. d is the dimension value of the sample space. x' signifies the sample value. k and j are the sample category and sample number, respectively. After outputting the hidden layer, the summation layer is used to weight the outputs of neurons belonging to the same type of hidden layer. The specific calculation process is shown in equation (6).

$$\zeta_k = \frac{\sum_{j=1}^{N} \varpi_{kj}}{N} \tag{6}$$

In equation (6), N signifies the number of samples in that category. ϖ_{kj} is a weighted value. ζ is the output result of the summation layer. The specific process of the proposed motion mode judgment method is shown in Figure 6.

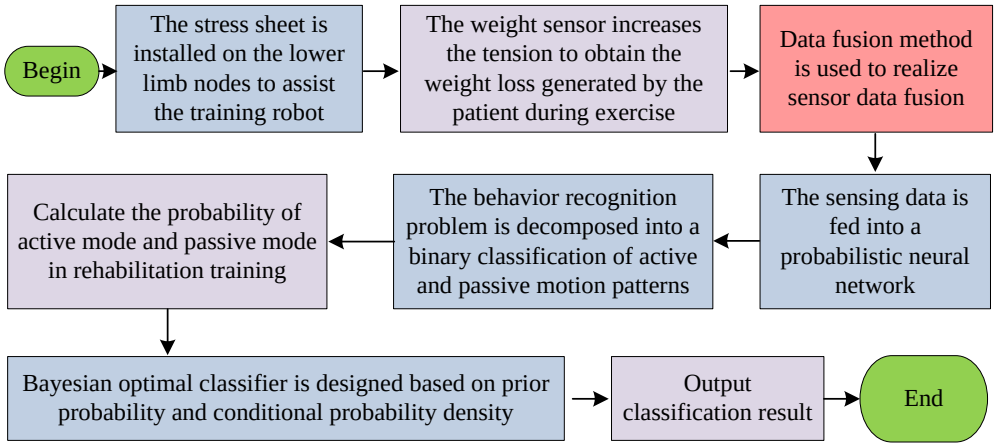


Figure 6: The specific process of the proposed motion mode judgment method.

As shown in Figure 6, the study inputs the interaction force data of each node and the data measured by weight sensors into the network model. The input variables also include the phase of each joint. These data are standardized after pre-processing steps to ensure that data of different dimensions can be compared at the same scale. These input variables can comprehensively reflect the dynamic state and motion characteristics. In the training phase, the research utilizes rich historical data to train the network to learn the mapping relationship between different motion patterns and sensor data. The probability density function for each motion mode is presented in equation (7).

$$f_{x,\gamma'} = \frac{(x-\gamma_i')^T (x-\gamma_i')}{2\varphi^2} \tag{7}$$

In equation (7), γ' signifies the connection weight. φ signifies the smoothing factor. $f_{x,\gamma'}$ is the probability density function for each motion mode. Based on the probability density calculation results, the motion mode

that best matches the current sensor data can be determined. Firstly, a large amount of rehabilitation training data is classified and labeled through the manual labeling method to ensure the accuracy and reliability of the data. The categories of motion intentions include standing, walking, sitting, standing, etc., and each category corresponds to a specific sensor data pattern. Subsequently, these annotated data are used for model training, gradually optimizing network parameters and improving recognition accuracy.

3 Results

To test the perception ability and application effect of the proposed mechanical dynamic perception model, a series of experiments are designed to analyze.

3.1 Analysis of data acquisition and processing effectiveness based on multi-modal perception and kalman filter

To test the perception ability and application effect of the method proposed in the research, simulation experiments and field operation experiments were designed for the research. The specific experimental setup process is shown in Figure 7.

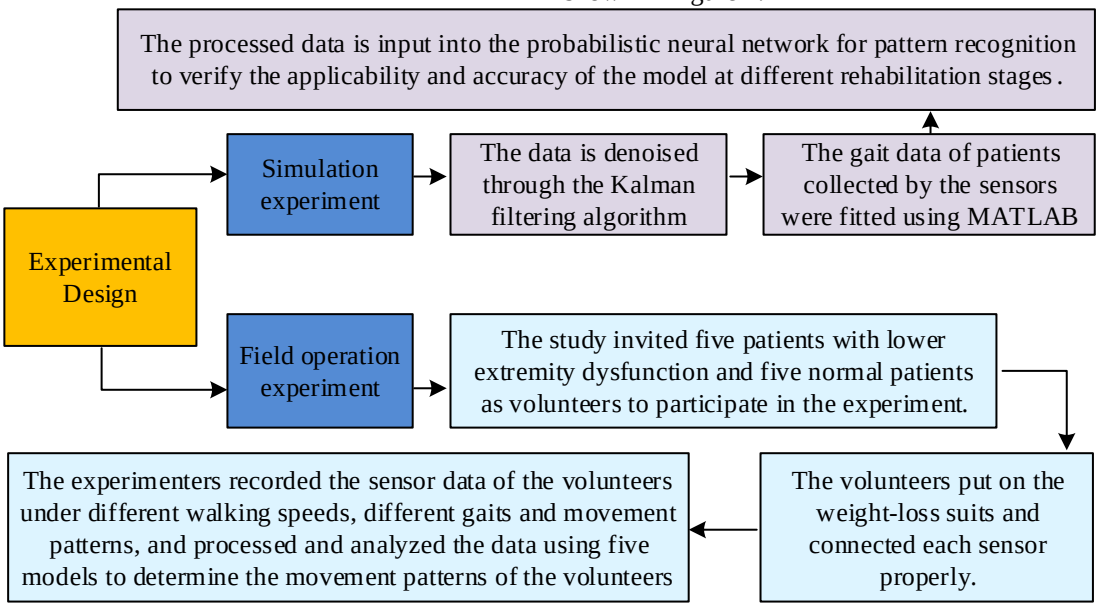
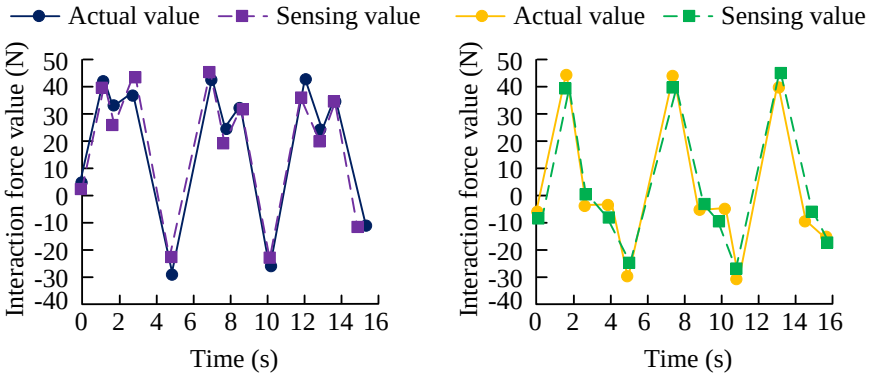


Figure7: The specific experimental setup process

As shown in Figure 7, the MATLAB was taken to fit the patient gait data collected by the sensor. Then, the Kalman filter algorithm was used to denoise data to ensure its accuracy and reliability. Subsequently, the processed data was input into the probabilistic neural network for pattern recognition to validate the applicability and accuracy of the model at different rehabilitation stages. In the field operation experiment, five patients with lower extremity dysfunction and five normal patients were invited as volunteers to participate in the experiment. During the experiment, volunteers put on weight-loss suits and correctly connected each sensor. Experimenters recorded sensor data from volunteers at different walking speeds, gaits, and motion modes, and used five models to process and analyze the data to determine the volunteers' motion mode. A total of 10 field operation experiments were conducted, each lasting for 30 minutes, to ensure the data diversity and repeatability. The patients were divided into two groups: normal patients and those with lower extremity dysfunction. They were grouped according to the severity of the patients' conditions and the rehabilitation stage to ensure the scientificity and comparability of the experimental results. The experimental results of the 10 patients did not differ much, and the results before and after the experiment were basically consistent.

To validate the accuracy of data collection from interaction force sensors, taking the rehabilitation training robot as an example, the patient gait data collected by the sensors is fitted using MATLAB. The simulation results of the exercise status of the same patient participating in rehabilitation training are compared with the actual measurement results collected by sensors. The results are shown in Figure 8.



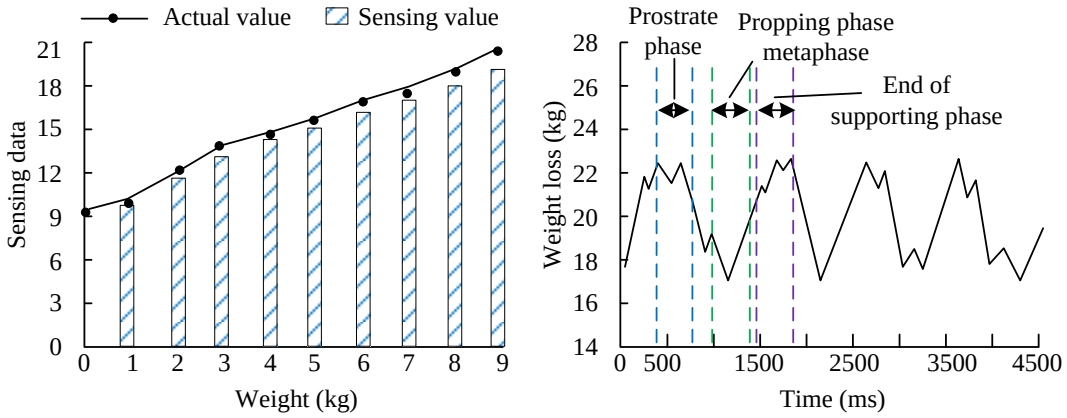
(a) Fitted curve of thigh interaction force value

(b) Leg interaction force fitting curve

Figure 8: Accuracy analysis of interaction force perception data.

In Figure 8 (a), the simulation results of thigh interaction force were basically consistent with the data curve collected by the sensor, reaching 0.95. As shown in Figure 8 (b), the simulation and measured data of leg interaction force also showed high consistency, further confirming the reliability of data collection.

Weight sensors were employed to determine the gait cycle of patients during the rehabilitation process, thereby assisting in dynamic perception. To validate the accuracy of the weight sensor installation method and the data reliability, a dummy model is used and weights of 1, 2, 3, 4, 5, 6, 7, 8, and 9kg are sequentially added to the dummy model to simulate patients of different weights. Then, the data from the weight sensor is collected at each weight. The original weight of the dummy is 10kg. The measurement results of four weight sensors and the changes in weight loss values of normal patients with walking status are shown in Figure 9.



(a) Four weight sensor measurements

(b) Change of weight loss value with walking state

Figure 9: Measurement curves of four weight sensors with different weights.

As shown in Figure 9 (a), with the increase of weights, the tension value detected by the sensor gradually increased, and the curve fitting between its measured value and the actual weight value of the dummy reached 0.97. As shown in Figure 9 (b), the measurement results of weight loss values also exhibited periodic changes over time. In the early stage of the supporting phase, the weight loss value gradually increased, which corresponded to the process of the patient gradually transferring their body center of gravity to the weight loss device. After entering the mid support phase, the weight loss value remained stable. At the end of the supporting phase, the weight loss value gradually decreased, as the patient begins to shift their body weight from the weight loss device back to their own legs. This indicates that the weight loss measurement of the weight sensor can further assist the robot in determining the current motion status of the patient.

3.2 Perception effect analysis based on multi-modal sensor fusion

To process the collected data and avoid interference noise affecting the accuracy of dynamic perception, the Kalman filter is used for data preprocessing. To validate the rationality of the proposed data processing method (Method 1), the study compares it with the currently popular data preprocessing methods. The comparative

methods include sliding average filtering (Method 2), median filtering (Method 3), and wavelet transform denoising (Method 4). The study first simulates sensor data containing different levels of noise, and then applies these four methods for preprocessing. The Mean Square Error (MSE) and R-squared (R value) of the interaction force perceived by the model after four processing methods are taken to evaluate the performance, as displayed in Table 3.

Table 3: Quality comparison of sensor data before and after noise reduction.

Project	SNR=10dB		SNR=20dB		SNR=30dB	
	MSE	R value	MSE	R value	MSE	R value
Method 1	0.05	0.93	0.03	0.95	0.01	0.97
Method 2	0.10	0.87	0.09	0.89	0.07	0.90
Method 3	0.09	0.88	0.08	0.90	0.06	0.91
Method 4	0.07	0.90	0.05	0.92	0.04	0.93
Method 5	0.12	0.85	0.11	0.87	0.08	0.88

As shown in Table 3, Method 1 outperformed other comparison methods on MSE and R-squared under SNR of 10dB, 20dB, and 30dB. Especially, at SNR=10dB, Method 1 had the lowest MSE of only 0.01 and the highest R value, reaching 0.97.

To further verify the rationality of the sensor fusion method, the study uses data before and after fusion for dynamic perception, judges the patient's motion mode, and compares the results. The accuracy and running time of the motion mode judgment of the research model before and after data fusion are shown in Figure 10.

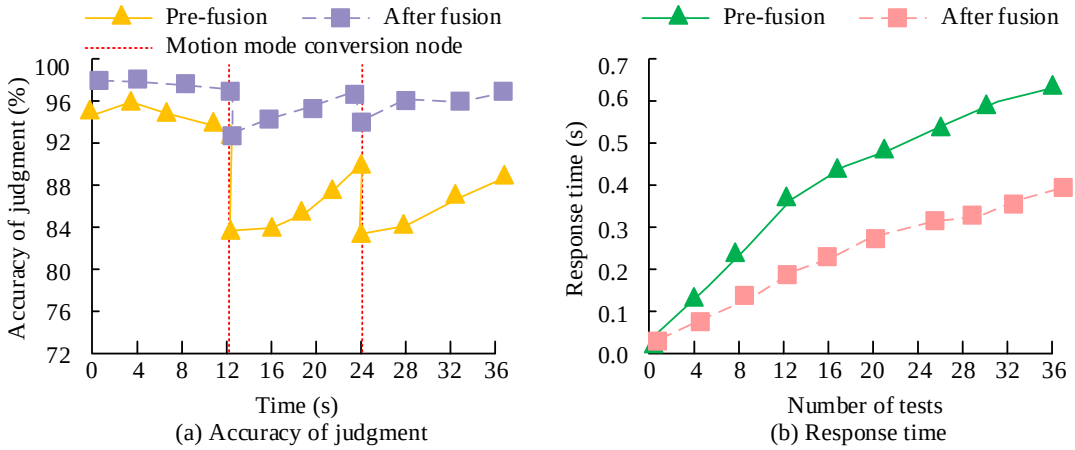


Figure 10: The accuracy and running time before and after the fusion data.

In Figure 10 (a), the accuracy of data judgment before fusion was relatively low. Especially at the patient motion mode transition, the model was prone to misjudgment, with an average accuracy of 85.47%. The fused data significantly improved the judgment accuracy, with an accuracy of 95.84%, which enabled more accurate identification of the patient's motion intention. As shown in Figure 10 (b), the model's running time was reduced by 0.28s after data fusion, indicating that the sensor fusion method not only improved the judgment accuracy, but also enhanced the running efficiency.

3.3 Analysis of the practical application effect of dynamic perception model

To test the performance of the proposed multi-modal perception fusion robot mechanical dynamic perception model (Model 1), a comparative experiment is conducted on Model 2 in reference [18], Model 3 in reference [19], Model 4 in reference [20], and Model 5 in reference [21]. Model 2 focuses on the adaptability of soft robot skin and enhances the interactive ability of collaborative robots through body tactile perception. Model 3 combines machine learning and artificial synapses to accurately respond to intelligent flexible sensing systems. Model 4 utilizes active visual tactile interaction to optimize object pose estimation. Model 5 is based on neural network assisted filtering to improve the robustness of multi-modal indirect sensing in soft robots. These five models are applied to the perception process of robot rehabilitation training. Five patients with lower limb dysfunction and five normal patients are recruited as volunteers to participate in the experiment. During the experiment, volunteers wear weight loss clothing and connect various sensors. The experimenters record the sensor data of volunteers at different walking speeds, gaits, and motion patterns, and use five models to process and analyze the data to determine the volunteers' motion patterns. The motion mode refers to active walking and passive walking for patients. Motion intention recognition

refers to accurately identifying the volunteer's motion intention, including actions such as starting, accelerating, decelerating, and stopping. The method for determining the ground conditions is to measure the ground reaction force through high-precision pressure sensors, capture the ground texture information in combination with visual sensors, and comprehensively judge parameters such as ground hardness and friction coefficient to ensure that the model can accurately identify the motion intention under different ground conditions. During the experiment, the accuracy of motion mode judgment for five models is recorded, and the results are shown in Figure 11.

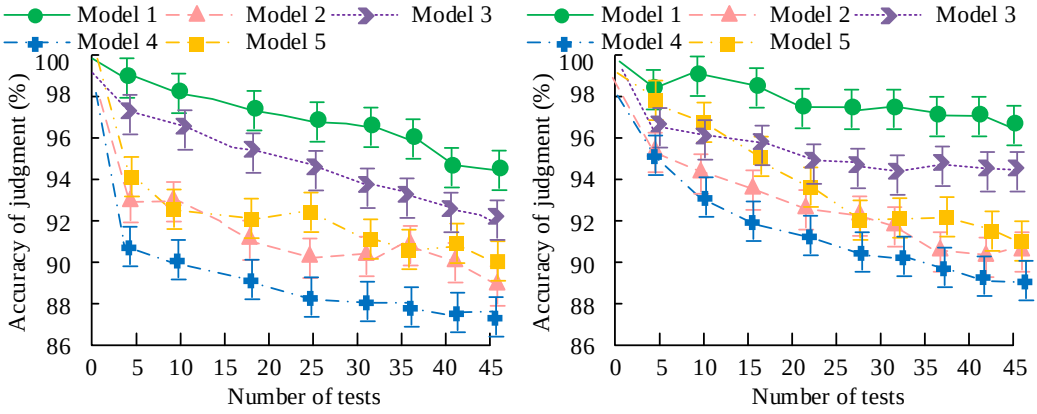


Figure 11: Motion mode judgment accuracy of five models.

In Figure 11 (a), the accuracy of each model in judging the motion mode of patients with lower limb dysfunction gradually decreased with the increase of testing times. However, the overall judgment performance of Model 1 was significantly higher than other methods, with a judgment accuracy rate consistently above 92%. As shown in Figure 11 (b), for normal patients, the accuracy of the five models was relatively higher, with Model 1 having the highest accuracy, at 96.88%.

To further test the practical application effect, volunteers were asked to judge their walking speed, gait characteristics, and motion modes during rehabilitation training in different scenarios, and the accuracy and stability were evaluated. The experimental scenarios include walking on flat ground, crossing obstacles, and going up and down stairs. Volunteers wear weight loss clothing and connect sensors to carry out rehabilitation training activities according to instructions. The accuracy and response time for each model in three scenarios are presented in Table 4.

Table 4: Motion intention recognition accuracy and response time of each model under three scenarios.

Project	Walking on flat ground		Crossing obstacles		Going up and down stairs	
	Intention recognition accuracy (%)	Response time (s)	Intention recognition accuracy (%)	Response time (s)	Intention recognition accuracy (%)	Response time (s)
Model 1	95.48±1.55*&%#	0.85±0.09*&%#	95.72±1.69*&%#	0.89±0.08*&%#	95.36±1.47*&%#	0.82±0.07*&%#
Model 2	85.69±2.43	1.62±0.12	85.71±1.40	1.68±0.12	85.65±1.68	1.77±0.14
Model 3	90.34±1.78	1.05±0.09	91.00±1.83	1.08±0.10	90.52±1.63	1.07±0.11
Model 4	83.54±1.49	1.81±0.10	84.00±1.74	1.82±0.12	84.11±1.72	1.80±0.13
Model 5	88.45±2.00	1.21±0.11	88.90±1.69	1.12±0.11	88.23±1.88	1.36±0.12

Note: In Table 4, * indicates that the comparison results between Model 1 and Model 2 are different (p<0.05). & Indicates that the comparison results between Model 1 and Model 3 are different (p<0.05). % Indicates that there is a difference in the comparison results between Model 1 and Model 4 (p<0.05). # Indicates that the comparison results between Model 1 and Model 5 are different (p<0.05).

According to Table 4, the intention recognition accuracy of Model 1 was significantly higher than the other four models in these three scenarios, reaching 95.48%, 95.72%, and 95.36%, respectively. Meanwhile,

the response time of Model 1 was relatively short, at 0.85s, 0.89s, and 0.82s respectively, indicating its high real-time performance. In contrast, the other models had lower accuracy in intent recognition and longer response time. Especially in complex scenarios such as crossing obstacles and going up and down stairs, Model 1 had more obvious advantages, with an intention recognition accuracy about 10% higher than other models and a response time shortened by nearly 50%. This indicates that Model 1 can quickly and accurately perceive the patient's motion intention, providing timely and effective auxiliary support for the robot. In addition, Model 1 has demonstrated good stability and adaptability, and can maintain high accuracy in different patients and rehabilitation stages.

To test the effectiveness of the proposed intent recognition model applying Kalman filtering and multi-sensor fusion in the research, ablation experiments are conducted on the model. The Kalman filter and sensor fusion modules are removed separately for testing. The comparison results are shown in Table 5.

Table 5: Ablation experiments of the intention recognition model

Project	Module			Accuracy (%)
	Kalman filter	Multi-sensor fusion	Basic model	
1	-	-	√	87.47
2	-	√	√	90.36
3	√	-	√	90.11
4	√	√	√	95.48

As shown in Table 5, when using the multi-sensor fusion or Kalman filter module alone, the model accuracy was improved, but did not reach the level of Model 1. The combination of the two can significantly improve the accuracy and real-time performance of intent recognition, verifying the effectiveness of the research method. Further analysis shows that Kalman filtering effectively reduces noise interference, while multi-sensor fusion enhances data integrity. The synergistic effect of the two significantly improves the performance of the model in complex scenarios.

4 Discussion and conclusion

Traditional rehabilitation training methods for lower limb dysfunction often rely on the therapist's experience and judgment, lacking objective and accurate evaluation methods. Therefore, a robot mechanical dynamic perception model based on multi-modal sensor fusion was proposed, providing a new solution for rehabilitation training of patients with lower limb dysfunction. A set of behavior recognition input variables was constructed by collecting patient interaction force perception data and weight loss value data. Afterwards, the probabilistic neural network was taken to recognize the patient's motion intention, assisting the robot to generate correct responses to the patient's motions. The fitting degree between the interaction force perception data and the measured data reached 0.95, and the data changes transmitted through the weight sensor could accurately determine the patient's motion phase. The R-squared of the data processed by Model 1 remained above 0.93 and the MSE did not exceed 0.05 at 10dB, 20dB, and 30dB. In practical applications, the perception model proposed in the research can accurately perceive the motion intentions of patients and thereby achieve accurate auxiliary training. Its average recognition accuracy reached 95.52%, and the average response time was only 0.85 seconds. The recognition accuracy of the other four models reached 95.48%, 95.72% and 95.36% respectively. The response time was 0.85s, 0.89s and 0.82s, respectively. Compared with these four models, the model proposed in the study has higher real-time performance and accuracy. The performance difference occurs because the research combines Kalman filtering and multi-modal data fusion technology, effectively reducing noise interference and improving the accuracy and efficiency of data processing. The Kalman filtering algorithm optimizes the sensor data in real time, ensuring the intention recognition accuracy. Meanwhile, multi-modal fusion enhances the adaptability of the model to different scenarios, enabling Model 1 to maintain excellent performance in complex environments. This indicates that the proposed model not only improves the accuracy of motion intention recognition, but also shortens response time, providing patients with more timely and effective auxiliary support. At present, the research has not considered eliminating signal interference through machine structures. In the future, mechanical structure optimization will be considered to further improve the accuracy and stability of data acquisition.

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Integrating Equation-Based Labeling and Classification for Adaptive Turkish Vocabulary Acquisition

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Keywords: adaptive learning, svm, behavioral analytics, vocabulary assessment, educational technology

Received: April 8, 2025

Traditional vocabulary evaluation techniques frequently emphasize correctness above behavioral indications such as attempts and reaction time. To overcome this gap, our study proposes a machine learning technique that combines behavioral analysis with linguistic insights to discover vocabulary gaps among Turkish language learners. A Support Vector Machine (SVM) model was constructed with a Radial Basis Function (RBF) kernel and refined via grid search to maximize hyperparameters (C=10, γ=0.1) using a dataset of 1,000 interactions from 20 students. Behavioral attributes such as attempt count, answer response time, and answer correctness were collected to quantify student uncertainty and engagement. The approach also integrates word difficulty levels and thematic categories. An equation-based labeling technique was first applied to identify vocabulary weaknesses, laying the foundation for subsequent machine learning classification. The findings demonstrated strong performance, achieving an accuracy of 89%, precision of 86%, recall of 91%, and an F1-score of 88%, surpassing linear and polynomial kernel alternatives. These results underscore the importance of behavioral metrics in adaptive learning systems and support scalable integration into mobile applications.

Povzetek: Članek predstavi pristop za prilagodljivo učenje turških besed z združitvijo enačbenega označevanja in SVM klasifikacije ob upoštevanju vedenjskih značilnosti, kot so čas, poskusi in pravilnost.

1 Introduction

Vocabulary acquisition serves as a fundamental aspect of language learning, impacting reading comprehension, communication fluency, and cognitive development. Traditional assessment methods frequently simplify proficiency to binary metrics correct or incorrect answers neglecting more nuanced behavioral indicators that reveal underlying learning gaps, including attempts, response time, and self-correction patterns. This oversight restricts the personalization of adaptive learning systems, which find it challenging to effectively address individual weaknesses. Recent advancements in educational technology highlight the potential of behavioral analytics to address this gap; however, limited research has systematically combined these metrics with linguistic features to enhance vocabulary assessments.

This research presents a machine learning framework that utilizes both behavioral and linguistic data to detect vocabulary deficiencies in learners of the Turkish language. Our model integrates attempt counts and answer attempts—metrics indicative of metacognitive uncertainty—alongside word difficulty and thematic classifications, in contrast to previous approaches that focus solely on correctness or response time. A Support Vector Machine (SVM) classifier using a Radial Basis Function (RBF) kernel was trained using a dataset including 1,000 interactions from 20 students. Grid search was used to maximize the model thereby striking a mix between generalizability and intricacy.

The findings demonstrate the framework's efficacy: the model achieved 89% accuracy, 86% precision, 91% recall, and an 88% F1-score, exceeding both linear and polynomial kernel options. The RBF kernel's capacity to encapsulate non-linear interactions, especially the synergistic impacts of attempts and erroneous replies on moderately challenging words, was essential to its efficacy.

The findings highlight the significance of behavioral analytics in converting static assessments into dynamic, adaptive instruments. Quantifying uncertainty through attempts and response patterns allows educators to obtain actionable insights into student cognition, facilitating targeted interventions that address not only the errors learners make but also the underlying reasons for their struggles.

So, the results show that the framework really works well! The model hit 89% accuracy, 86% precision, 91% recall, and an 88% F1-score, which is better than the linear and polynomial kernel options. The RBF kernel demonstrates strong capability in capturing complex non-linear interactions, particularly in modeling how multiple

attempts and incorrect responses influence the classification of medium-difficulty words, an aspect that significantly contributes to its superior performance.

2 Related works

2.1 Automated label assignment in machine learning

Automated label assignment has evolved as a required component of machine learning since it solves the challenges of manual annotation, often labor-intensive, inconsistent, and expensive. Although traditional approaches mostly rely on human input to classify data, as datasets get more complex and demand accurate and fast automated labelling techniques have grown. Recent advances in artificial intelligence have brought a spectrum of techniques ranging from rule-based systems to deep learning-driven label propagation to improve both efficiency and accuracy in many spheres.

One main application of automated labelling is geospatial analysis since large-scale datasets in this field demand efficient annotations. Albrecht et al. presented AutoGeo Label, a system designed to generate labels for remote sensing data, using statistical elements taken from LiDAR studies. Almost 90% of their methods proved the efficiency of automated labelling in large geospatial databases [1]. Bobák et al. proposed a reinforcement learning method for data visualization and mapping as a means to optimize point-feature labeling positioning, the authors used scenarios of medical atlases and geographic maps while demonstrating that the performance was higher than traditional, hand-designed labeling methods [2].

In image classification tasks, contradictory data may cause inconsistencies during hand labelling, Schmarje et al. introduced Clever Label as a proposal-driven labelling approach aimed at reducing costs and errors during labelling. A 30% cost reduction on labelling costs was established without compromising the quality of the annotations, thus demonstrating the value of semi-autonomous technology in maximizing human efforts [3].

Another vital technique in automated labelling is label propagation—where labels are assigned based on data point relationships. This methodology has been particularly employed in scenarios with constrained labeled data, as it facilitates the transmission of labels from neighboring events (Label Propagation Algorithm). Zhang et al. analyzed machine learning techniques employed for the annotation of text, audio, and video data within a comprehensive evaluation of auto-labeling technologies [4]

Their work underlined the growing need for automated annotations in big-scale datasets, especially in disciplines including natural language processing and computer vision [5].

Automated labelling has also shown great value in medical imaging as well in reducing dependence on hand annotations. Stember and Shalu developed an automated label extraction from clinical reports combined with a deep reinforcement learning system to classify 3D MRI brain scans. Their analysis revealed that machine learning models could achieve high classification accuracy even with limited training data by using automated label extracting techniques [6].

These studies taken together reveal the ongoing variation in automated label assignment in many domains. In geospatial analysis, image classification, object detection, or medical imaging, advances in machine learning keep stretching the limits of labelling accuracy and efficiency. Still, there is work to be done refining these methods to guarantee dependability, adaptability, and generalization over many datasets. Future research should focus on dynamically improving label quality by combining equation-based heuristics, machine learning classification, and user interaction data.

2.2 Machine learning classification in educational applications

Machine learning categorization has emerged as a powerful instrument in educational applications, facilitating more effective and tailored learning experiences. These methodologies have been utilized in several areas, such as monitoring student progress, predicting academic success, developing adaptive learning systems, and ensuring equity in educational examinations. Employing machine learning will enable educational institutions to forecast learning results, provide tailored support for each student, and develop systems that cater to their specific needs.

Another significant application is the prediction of academic success. Zhang et al. employed machine learning classifiers to predict students' academic outcomes based on their intrinsic desire, autonomy, and other learning techniques. Tree-based models, including random forests, had exceptional performance, achieving an accuracy of 94.9%, as reported in their study. Preliminary forecasts of student performance enable educators to implement targeted interventions, offer personalized assistance, and ensure students stay on track. This technique optimizes learning while simultaneously enhancing overall student retention rates [7].

Recent studies published in Informatica have further explored classification techniques in educational settings. For example, Kaur et al. proposed an ensemble voting–based model to predict online student academic performance, demonstrating that combining multiple classifiers can significantly improve early identification of at-risk learners [8]. Likewise, Wang detailed a scalable Naive Bayesian–driven system for the automatic classification of massive academic document collections, highlighting its high accuracy and efficiency for organizing educational resources [9].

One significant aspect that has been significantly impacted by machine learning classification is ensuring fairness in education examinations. Sulaiman and Roy investigated the application of transformer neural networks in education for more meaningful representation of tabular data for fair decision-making. Their paper illustrated that transformer models had the capacity to

trade off accuracy and fairness, thereby enhancing equal treatment of students from diverse groups in performance assessment. This is especially critical in high stakes testing situations where bias compromises the fairness of assessment [10].

Moreover, artificial intelligence has become rather helpful for people with disabilities. For people with dyslexia, AI-driven tools including chatbots and word prediction software help to improve reading and writing skills. These technologies help students with learning challenges to efficiently interact with the curriculum and close achievement gaps with their peers. Though there are concerns about depending too much on artificial intelligence, these technologies have helped students finish tasks that would otherwise be difficult or impossible. Moreover, artificial intelligence is growingly important for automating teacher administrative tasks. The government of the United Kingdom has started projects to help teachers assess homework and assignments by using artificial intelligence software.

The fields of education are currently more than ever influenced and affected by using machines. This is also the technology that promotes creating learning solutions that are more flexible, adaptable, and with guaranteed results. It is through the means of predicting end results that it ensures justice, helps students who have different learning needs, and offers a more personalized learning experience.

Researchers and Educational institutions are embarking on the road to the realization of these methods while being aware of the broader implications in the field of education that integrating machine intelligence into the educational programs can bring.

2.3 Vocabulary learning and user behavior analysis

Mastering a new vocabulary by the learner is for sure a great part of the language learning process and the formation of direct to the learners' capability to understand a conversation. and communicate accurately. Typical vocabulary earning methods such as rote memorization have often been shown to be ineffective and uninteresting for the student. However, the development of these modern machine learning methods has made it possible to adapt them for the individual learner according to his/her performance. The methods selected here are the most suitable because they are not only dynamic but also adaptive and data-driven and they can easily be implemented into your daily language learning experience.

One model study that caught our attention was the one by Shin and Park in 2021 where they came out with a Pedagogical Word Recommendation (PWR) system that picks out a learner's knowledge of some words based on those words' connections with others of the same kind. The system gets information from the Intelligent Tutoring System, and it is a tool that is used by more than ten million learners who are preparing for the TOEIC exam. To predict vocabulary knowledge of the user, the system tracks vocabulary knowledge from a record of time and recommends words that are most relevant to the user's needs, offering the user a customized learning experience. This method not only involves user behavior but also it plays a vital role in this kind of teaching by proposing only the words that are parallel with the learner's ability to learn [11].

Closer yet to the telltale signs of artificial intelligence in vocabulary learning, a thesis tackled the tools used to forecast students' cognitive states while they are involved in a vocabulary tutoring system. The analysis of behavioral and linguistic data was the approach taken in the study to speculate off-task behaviors and to secure partial word knowledge based on open-ended responses. The insights obtained were to be used in designing personalized curricula which, in turn, should have a positive impact on the system's ability to provide tailored vocabulary exercises and amplify learning efficiency.

These studies together are promising in the wake of the union of artificial intelligence and user behavior analytics. One-way Learners will learn best if they receive customized learning experiences that meet their linguistic abilities. Thus, these new approaches to vocabulary teaching are devoid of the dullness of mere memorization and thus provide learners with more interesting and productive vocabulary learning experiences.

2.4 Summary and research gap

Based on big datasets, several studies including Zhang et al. [7] and Shin & Park [11] have significantly improved their predictions of academic performance and word knowledge. These methods, however, sometimes ignore the dynamic character of learner behavior by concentrating just on static data. For example. Shin & Park [11] missed including real-time behavioral data, so restricting their generalizability across various learner populations even though they used neural collaborative filtering for pedagogical word recommendation.

Furthermore, underlined in studies including Bobák et al. [2] and Albrecht et al. [1] the use of machine learning for tasks including label placement and automated labeling in geospatial data. These models failed to consider behavioral elements in their applications even if they were successful in optimizing processes and attaining great accuracy. This draws attention to a field gap since many models depend mostly on pre-computed labels or predefined inputs, so leaving little space for real-time changes depending on dynamic behavior.

By including behavioral traits into vocabulary classification for Turkish students, our work fills in this void as described in the last row of the table. Using behavioral measures will help us to identify vocabulary category gaps with greater accuracy (89%) and recall (91%), so making a fresh contribution to the field. One major constraint still is the lack of behavioral data in previous studies, especially in relation to vocabulary acquisition in several learning environments and fields.

2.4 Methodology

This study aims to improve the detection of vocabulary categories weaknesses in Turkish language learners by integrating behavioral attributes such as attempts times and the response time before choosing the final answer in addition to use the answer correctness and the word

Table 1: Comparison of the key studies discussed in related works

Study (Year)	Dataset	Problem Focus	Model/Method	Key Results	Limitations/Gaps
Zhang et al. (2022) [7]	Academic data of engineering undergraduates in China	Predicting academic performance of engineering undergraduates	decision tree (DT), Gradient boosting decision tree (GBDT) and random forest (RF)	RF model identifies 80%+ low-risk students by the end of the 2nd semester	Limited scope (one department/university), ignores behavior attributes, data imbalance, and low interpretability
Shin & Park (2021) [11]	Pedagogical Word Recommendation (PWR) dataset: 36.1 million entries	Predicting word knowledge from encountered words; formalizing pedagogical word Recommendation	Neural Collaborative Filtering (NCF) approach	Feasibility of personalized vocabulary recommendation; large-scale self-reported dataset for benchmarking	No real-time behavioral data integration, limited to TOEIC learners, affecting generalizability
Bobák et al. (2023) [2]	Geospatial/medical maps; real-world datasets, compact dataset, and IATA airport codes with 250 anchors.	Automated label placement	Reinforcement Learning with Multi-Agent Deep Reinforcement Learning (MADRL)	Optimized label positioning	Increased computation time; more suitable for pre-computed labeling, not real-time applications
Albrecht et al. (2021) [1]	Remote sensing data, including LiDAR, processed via IBM PAIRS platform	Automating label generation for geospatial tasks like land use classification and object detection	Big data processing pipeline utilizing rasterized statistical features from surveys	Multiple classes generated with ~0.9 accuracy	Domain-specific, lacks behavioral metrics, depends on input data quality
Schmarje et al. (2023) [3]	Multi-domain image classification benchmark with ambiguous labels	Enhancing annotation efficiency and quality for ambiguous image classification tasks	CleverLabel (proposal-driven)	30% cost reduction	Focused on images, Potential bias introduced by proposal-guided annotations, and reliance on the quality of initial proposals.
Stember & Shalu (2022) [6]	3D MRI brain scans	Automated label extraction from clinical reports for 3D MRI brain volume classification	Deep Reinforcement Learning	High accuracy with limited labels	Clinical imaging challenges: generalizability, data quality variability; specialized in 3D MRI, limited the to medical field.
Sulaiman & Roy (2022) [10]	Educational domain dataset	Fair classification in the educational domain	Transformer neural networks	Balanced accuracy/fairness	Challenges in defining fairness metrics for educational classification
Our Work	Turkish learners (N=20, 1k interactions)	State vocabulary category gaps via behavioral attributes	SVM-RBF (C=10, γ=0.1)	89% accuracy, 91% recall	**Novelty:** employ behavioral metrics to classify vocabulary weaknesses across word categories

difficulty to assess this weakness, according to that, the study uses a hybrid technique by an equation-based method for initial label assignment, then a machine learning classification model dynamically predicts labels depending on the collected behavioral attributes during vocabulary exercises in the Turkish language provided by the applicable system. Figure 1 shows the six main phases of development of this method: data preparation, equation-based initial labeling, predicting new labels using classification, Training and generating the base model, Model evaluation and Enhancements, and Integrating model in the learning system.

The following summarizes the main phases of the approach:

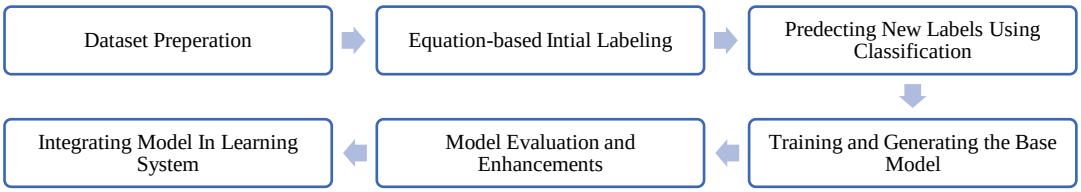


Figure 1: Research methodology

2.5 Data preparation

2.5.1 Dataset initial collection

In this stage, we have accumulated interesting and various definitions of the most frequently used Turkish words that were collected from credible linguistic sources like frequency lists and corpora. These words have each been divided into 36 separate groups, which point to the different thematic areas, which are Education, Family, Technology, and Health, among others. This assignment was carried out to facilitate learning by the division of vocabulary. Thus, the words were put into levels based on the difficulty, by considering the phonetic property that if words are those with more complex sounds or structures the task will be difficult and if words are those with a few syllables the task will be simple.

2.5.2 Adding behavioral attributes

Based on this dataset, we developed a simple application designed to test vocabulary knowledge by presenting Turkish words along with their meanings in the form of four multiple-choice options in English. The application was developed to provide immediate feedback to the students after they selected an answer, indicating whether their choice was correct or incorrect. A group of 20 participants were involved in the testing phase. Each student answered 50 questions, covering a variety of vocabulary words across different difficulty levels and categories. The students were selected from diverse backgrounds, ensuring a mix of proficiency levels in the Turkish language. This resulted in a total of 1000 rows in the dataset (20 students × 50 questions). Prior to participation, informed consent was obtained from all students, and participation was entirely voluntary. All collected data were anonymized to protect individual identities, and no personally identifiable information was stored. Additionally, care was taken to minimize potential biases by ensuring diversity in participant selection and by maintaining balanced representation across different language proficiency levels.

During this stage, we collected a range of behavioral data to analyze student performance and learning patterns. The data collected included:

Answer: Whether the student's response was correct or incorrect, providing the core measure of their knowledge.

Number of Attempts: The number of times a student hesitates before selecting their final answer. This helps gauge their confidence in selecting the correct answer.

Response Time: The total time taken by each student to arrive at the final answer. This helps assess the ease or difficulty a student faces when processing the question.

Number of Attempts: The number of times the students changed their answer before settling on the final one, indicating uncertainty or difficulty in choosing the correct option. This rich behavioral data allowed us to better understand student learning patterns and provided valuable insights into how students interact with vocabulary questions based on their proficiency level and the difficulty of the words. Thus, our dataset was completed, Table 2 presents a sample of the dataset used in this study, showing the words, their classifications, and behavioral data, such as correctness, response time, and attempts count during the vocabulary tests.

1. Numeric encoding

During this step, we converted categorical and behavioral data into numerical values to facilitate analysis and the training of machine learning models. Numeric encoding is an essential phase in data preparation for algorithms, as the majority of machine learning models necessitate numerical inputs for optimal processing.

2 Word and category encoding

- **Word ID:** Every word is allocated a distinct identity, facilitating dataset optimization and enabling effective management in machine learning models.

- **Category ID:** The Category of each word (e.g., Education, Family) is substituted with a number identifier for enhanced processing efficiency.

Table 3 below demonstrates the transition from the original categorical values to their corresponding numeric representations:

Table 3: Dataset first form sample

Word	Category	Answer	Difficulty	Response Time (seconds)	# Attempts
"Öğretmen"	Education	Correct	Easy	3.2	0
"Aile"	Family	Correct	Easy	2.0	0
"İnşaat"	Work/Occupation	Incorrect	Medium	5.0	1
"Ev"	Home	Correct	Easy	2.5	0
"Okul"	Education	Correct	Easy	3.0	1

Table 2: Final dataset form

Word	Category	Answer	Difficulty	Response Time (seconds)	Attempts #
1	1	1	1	3.2	0
2	2	1	1	2.0	0
3	3	0	2	5.0	1
4	4	1	1	2.5	0
5	1	1	1	3.0	1

3 Answer encoding

The "Correct/Incorrect" responses were quantified numerically:

- Correct: 1
- Incorrect: 0

This binary encoding enables the system to categorize responses as numerical values instead of text.

4 Difficulty level encoding

To more accurately represent the level of difficulty, the "Difficulty" classification was converted into numerical values::

- Easy: 1
- Medium: 2
- Hard: 3

This encoding enhances the model's understanding of word difficulty, hence enabling a more precise analysis of student performance assessment.

5 Behavioral data encoding

- **Response Time (seconds)**: This column represents the time a student took to answer each question. The time is kept as a continuous numeric value (in seconds) for further analysis.
- **Attempts #**: This is also represented as a numeric value, capturing how many times the student hesitated before finalizing their answer. The higher the number, the more uncertain the students were about their answer.

Upon finalizing the dataset and converting it into a numerical format, we may go to the second step, which entails the preliminary label assignment based on a numerical equation. This equation will be elucidated in depth in the subsequent phase.

2.6 Equation-based Initial Labeling

Using rule-based equations for initial dataset labeling offers several advantages, especially in leveraging domain expertise, efficiency, and interpretability. Rule-based systems can encode expert knowledge and domain-specific rules effectively, ensuring that initial labels are grounded in well-established principles [12,13]. Experts can define precise rules based on their understanding, leading to high labelling accuracy. Additionally, rule-based systems can quickly label large datasets without extensive computational resources, making them useful for real-time data or large volumes of data. Automation allows consistent criteria application across the entire dataset, reducing manual effort and potential human errors [14]. The straightforward nature and clarity of rules promote a transparent labeling process, thereby aiding in validation and auditing [15].

Rule-based labels establish a robust foundation for training machine learning models, facilitating the initiation of the learning process with a dependable set of labeled data.

Combining rule-based initial labeling with machine learning refinement leverages both approaches, as the rule-based system provides a reliable starting point while machine learning uncovers more complex patterns and improves accuracy over time [16].

When building the main equation that employed a rule-based approach we consider four important parameters to be in this equation: the correctness of answers, the amount of time spent on the questions, the attempts times, and the difficulty level of the questions, to identify a user's weak points when learning Turkish. Every parameter is assigned a weight according to its

significance, and max value which indicate percentage of user behavior across all the dataset's rows that are captured and then we can judge which a user is deemed weak or not as mentioned in equation 1 and clarified in the equation's sample below.

Equation 1: Rule-based labeling equation

$$\begin{aligned} \boldsymbol{Weakness\ Score} &= \boldsymbol{w}\mathbf{Correct} \\ &\times (1 - Correct\ Answer) \\ &+ \boldsymbol{w}\mathbf{Time} \times \frac{Time\ Spent}{\mathbf{Max\ Time\ Spent}} \\ &+ \boldsymbol{w}\mathbf{Attempts} \\ &\times \frac{Attempts\ Times}{\boldsymbol{Max\ Attempts\ Times}} \\ &+ \boldsymbol{w}\mathbf{Difficulty} \times \frac{\text{Difficulty}}{\boldsymbol{Max\ Difficulty}} \end{aligned}$$

- **wCorrect**, **wTime**, **wAttempts** and **wDifficulty** are the weights for each parameter, the summation of weight's attributes must equal 1.
- **Max Time Spent**: is the maximum time spent among all entries.
- **Max Attempts Times**: are the maximum number of Attempts times among all entries.
- **Max Difficulty**: is the maximum difficulty value among all entries.

The weakness score concludes with number between 0 and 1, if the weakness is greater than 0.5 so there is weakness in the vocabulary learning, and if it's less than 0.5 that's means the vocabulary is known to the student. To assign weight values effectively for this equation, consider the following four steps:

2.6.1 Define weight ranges

At this stage, it is essential to note that the sum of the four weights (wCorrect, wTime, wAttempts and wDifficulty) must equal 1. An initial assignment of these weights should then be established. For example, a uniform value of 0.25 for each weight can serve as a starting point. This value has been tested, and based on manual evaluation of the results, we found that there are more suitable methods for assigning these weights. These adjustments are elaborated in the following step.

2.6.2 Assign relative importance

At this stage, we made several adjustments to the weight values by analyzing each weight individually. For instance, the weight associated with whether the answer is correct is among the most critical factors that must accurately calibrate the equation. The duration of time spent is of moderate significance, as extended periods do not inherently signify a deficiency in word recognition; instead, they may indicate a more profound contemplation and analysis aimed at identifying fewer common terms. The weight associated with attempts, indicated by the frequency of a student's oscillation between answers, is significant as it reflects a lack of confidence and a propensity to guess prior to arriving at a final answer.

As for the final weight, which pertains to word difficulty, it is moderately important as well, since it often ties to the student's analytical ability to decipher syllables. This ranking of factors allows us to propose approximate values for each weight, which will be detailed in the subsequent step.

2.6.3 Adjust weights

In this step, we propose approximate weight values based on the analysis outlined in the previous step. These values are as follows:

- wCorrect = 0.4: Reflecting the critical importance of correctness in the equation.
- wTime = 0.2: Assigned moderate importance to account for thoughtful analysis rather than weakness.
- wAttempts = 0.3: Highlighting the significance of attempts as an indicator of uncertainty.
- wDifficulty = 0.1: Assigned moderate importance to acknowledge the influence of word complexity while not overemphasizing it.

These values serve as a starting point for further refinement and validation through testing and analysis.

To address potential concerns regarding the empirical nature of Equation 1 and to assess its stability, a sensitivity analysis was conducted and is presented in Appendix A. This study methodically assesses the effect on the labeling efficacy of changing the assigned weights (e.g., wCorrect, wTime , wAttempts and wDifficulty). The results show that, in the absence of human-labeled ground truth, the weakness score equation stays strong across many configurations, so supporting its dependability as the basis for machine learning-based refinement.

2.6.4 Testing and fine-tuning

During our testing, we initially utilized the suggested weight values on sample datasets and performed computations for the weakness scores. The preliminary results were juxtaposed with anticipated outcomes to ascertain the accuracy of the reported deficiencies. This method involved the verification of scores by educators and subject matter experts to ensure they accurately reflected realistic and significant evaluations of student understanding. There were stronger links between some traits, like time involvement and resistance, and mistakes in the dataset than to others when the study looked at the results. We changed our weights because of what we found. The time spent and questions were lowered to 0.25 because these seemed to better show where students were having trouble. Our study investigated the potential application of adaptive weights contingent upon the difficulty level of the words. In our analysis, we observed that emphasizing attempts and the duration of time spent was more predictive of uncertainty when using simpler words. For more challenging words, we emphasized correctness, as students' capacity to accurately identify difficult terms was a crucial determinant of their knowledge level. This adaptive method enabled the refinement of weights and enhanced the precision of weakness scores across varying levels of difficulty.

We employed adaptive weights to dynamically adjust the weights allocated to wCorrect, wTime, wAttempts, and wDifficulty across various elements. This technique facilitates the evaluation process to adapt based on certain parameters, including the difficulty level of the assessed word or the overall student performance. This approach ensures that the evaluation model remains adaptable and responsive to various circumstances.

2.7 Identifying the most match classifier

2.7.1 Labeling target clarification

The output of Equation 1 is a continuous Weakness Score assigned per interaction, ranging from 0 to 1. To prepare the dataset for supervised classification, this score was thresholder at 0.5 to generate a binary label per row:

- 1 indicates the presence of weakness (Weakness Score > 0.5),
- 0 indicates the absence of weakness (Weakness Score ≤ 0.5).

These binary labels were then used as the target variable for all classification models, including SVM. While average weakness scores per category were computed for analysis and personalized feedback, they were not used as labels in the machine learning training phase.

2.7.2 Classifier selection strategy

A variety of classification methods are used that comprise Naive Bayes [17], Support Vector Machines (SVM) [18] and k-Nearest Neighbors [19]. The characteristics which are specific to each method and which in different cases might make them more or less advantageous are the type of the application and the characteristics of the data.

SVM is still efficient in high dimensions and, generally, is less likely to overfit, particularly when there is a clear margin of separation. However, their computing demands can be substantial when dealing with huge datasets [18]. K-Nearest Neighbors (k-NN) is simple and very easy to learn. It uses a distance measure to classify data points. However, its performance can drop with large datasets and even more so with high-dimensional data [19].

Naive Bayes classifiers are predicated on Bayes' theorem and are generally very effective for classifying text and other problems with categorical input variables. However, the naivete assumption that the models make, requiring independence between features, can limit their usefulness [17].

Neural networks, including deep learning models, have a great ability to capture complex patterns and relationships in the data; however, training them requires a very large amount of data and computing resources [10].

Among the various techniques, Support Vector Machines (SVM) are an appropriate option for re-labeling the dataset following the initial rule-based method, owing to their capacity to model complex, non-linear relationships between features and their resilience to noisy data [20]. The rule-based system offers a fundamental labeling method; however, it is constrained by its inflexibility and lack of adaptability to complex patterns or interactions among features. Support Vector Machines (SVM), particularly when utilizing a Radial Basis Function (RBF) kernel [21], can identify and utilize complex relationships within the dataset, including the interactions among Time spent, attempts Times, and various numerical attributes. This capability guarantees that the re-labeled data captures nuances overlooked by rule-based logic. Furthermore, SVM demonstrates superior performance with numerical datasets characterized by attributes of differing scales, provided that appropriate feature scaling is applied [22]. Re-labeling with SVM enhances the system's accuracy and reliability, thereby validating and refining the initial rule-based labels.

To summarize, although many classification methods have their own merits, SVM is the most suitable choice for our dataset. Because it handles both linear and non-linear relationships through kernel functions ensures it can capture complex patterns in the dataset. Additionally, SVM's robustness to noise and overfitting makes it ideal for datasets, which include diverse numerical features such as Correct Answer, Time spent and attempts Times. By leveraging its strong generalization capabilities and adaptability to new data, SVM provides a scalable and efficient solution for improving labeling quality. This ensures more accurate relationships and insights, ultimately enhancing the reliability of the dataset and the performance of downstream applications.

2.8 Training and generating the base model

2.8.1 Train test split

Datasets are typically divided into two groups, a training set, and a test set. The training set is used to create the model and allows the decision tree to learn from the data to understand patterns and relationships. The test set is used to assess the model’s performance on data that it has not been trained on and provides an unbiased estimate of how well the model will generalize. One common way to divide the dataset is cross-validation; one of the more common approaches in this process is Stratified Random Split. Stratified random splits create splits in such a way to keep the distribution of classes (labels) as equal as possible between the training and testing datasets. This is extremely important for imbalanced datasets (When one class is under-represented). Stratified sampling keeps the proportions of each class the same in the training and test splits, which reduces the bias that can occur when classes are unevenly distributed across the splits.

2.8.2 Model training

Initially, the built-in functionality of the PHP-ML [23] library was utilized to develop a model employing Support

Vector Machine (SVM) as the classification method. The initial step in this process involved importing the required classes from the specified library, with a focus on the SVC (Support Vector Classification) class, which is utilized for SVM-based classification models.

To ensure the data structure was appropriate for training the model, the dataset had to be preprocessed to include relevant features while omitting unnecessary features. Once the data set was prepared, we then instantiated the SVC class, which we used to fit the SVM model on the labeled training data through the train () method.

In Appendix C we provide a thorough review of the preprocessing pipeline, hyperparameter grid search ranges, and the exact SVM training configuration to support repeatability. The PHP-ML library was used for implementation; additionally included for reference is the complete pseudo-code for data preparation and model training.

2.8.3 Model evaluation

In machine learning, evaluating the performance of a classification model is crucial for understanding its effectiveness. Common evaluation metrics include Accuracy, Precision, Recall, and F1-Score. These metrics help assess how well the model makes predictions and can guide further improvements. Below, we define each metric, provide the corresponding equations, and explain how to implement these metrics using PHP-ML.

- **Accuracy**

Accuracy is the most straightforward metric, representing the proportion of correct predictions made by the model [24]. It is defined as the ratio of correctly predicted instances to the total instances.

The model has an overall accuracy of 89%, which means it could correctly predict the existence or absence of language deficiencies in students 89% of the time. This very high accuracy indicates that the model was able to generalize well over a wide range of student actions and word levels. For instance, it consistently differentiated between students who provided confident answers with brief response times (e.g., "Aile" responded correctly in 2 seconds) and those who encountered difficulties (e.g., "İnşaat" answered incorrectly with a response time of 5 seconds and 1 attempts). The performance across classes is balanced, as indicated by the similar counts of true positives (182) and true negatives (176) in the confusion matrix. This suggests a level of robustness despite minor class imbalances, with a distribution of 55% for "weakness" and 45% for "no weakness." This metric highlights the model's practical application in real-world educational contexts, where consistent performance is essential for personalized learning interventions.

- **Precision**

Precision, also known as positive predictive value, measures the proportion of positive predictions that are actually correct which are calculated [25]. It is especially important when the cost of false positives is high.

The model attained an accuracy rating of 86%, demonstrating its effectiveness in accurately identifying true deficiencies and minimizing false positives. Specifically, 86% of students identified as having a deficiency, such as in the areas of "Technology" or "Work/Occupation," required additional practice. For example, if the model flagged a deficiency associated with seemingly heavy delays (e.g., 2 tries) and length of time (e.g., 5 seconds on “İnşaat”), the body of evidence is 86% accurate. The 14% that would be false positives could be attributed to edge cases, such as students who are overly analyzing simple phrases or rushed themselves through corrections. The model's high accuracy can give educators confidence in the suggestions, potentially reducing time needed for unnecessary assessment, and advancing the aim of efficient, targeted learning support.

- **Recall**

Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that are correctly identified by the model [26]. It is important when the cost of false negatives is high.

The recall score of 91% demonstrates that the model was effective during the test to capture nearly all true weaknesses, indicating that the number of students that would have gone unserved that would benefit from additional help would drop considerably. For instance, the model identified 91% of students that struggled with phonetically difficult words (e.g., difficulty level 3). or displayed attempts while reading (e.g. high readings of attempts). The model's false negative rate was low (9%), suggesting that true mistakes were infrequent (e.g. a student guessed the word correctly after one attempt but provided attempts). Having high recall is important in educational settings because if a student's weaknesses are not discovered, support is unlikely to be provided. The recall metric supports the instrumentation aligning with pedagogical priorities. Specifically, the instrumentation meant no learner could “slip through the cracks.”

- **F1-Score**

The F1-Score is the harmonic mean of Precision and Recall. It balances the trade-off between Precision and Recall, making it a useful metric when there is an

imbalance between the two [27]. The F1-Score is particularly helpful when both false positives and false negatives are costly.

The 88% F1-score, a harmonic mean of precision (86%) and recall (91%), denotes performance that is balanced and strong. This metric is important when considering the class imbalance of the dataset, and the purpose of the work in the real world, which is to balance accuracy (to avoid false alarms) and coverage (to avoid potentially missing vulnerabilities). The model exhibited strong performance when behavioral features, such as response time and Attempts, interacted with word difficulty. Further validation using bootstrap resampling confirmed that model performance remained stable under sampling variability. Please refer to Appendix B for full statistical details.

This was particularly evident when incorrect answers were given for medium-difficulty words following a 5-second interval. The similarity between the F1-score and the accuracy score of 89% indicates the model's consistency, suggesting that there is no over-prioritization of one class at the expense of recall for precision. The model's consistency allows for reliable application in adaptive learning systems, where a detailed tracking of student engagement and decision-making necessitates a corresponding level of granularity in evaluation.

- **Confusion matrix and ROC analysis**

To provide a more granular view of model performance across the two classes (weak vs. non-weak), we computed a confusion matrix and the Receiver Operating Characteristic (ROC) curve based on the validation data.

With rather low false positive and false negative counts, the confusion matrix, Table 4 shows a balanced distribution of true positives and true negatives. With an Area Under the Curve (AUC) score of 0.93, the ROC curve, Figure 2 exhibits strong discriminative capability, so indicating great sensitivity and specificity.

These results support the robustness of the model not only in overall accuracy but also in its ability to minimize misclassification across both classes.

Table 4: Fold confusion matrix

	Predicted Weak	Predicted Not Weak
Actual Weak	182 (TP)	18 (FN)
Actual Not Weak	24 (FP)	176 (TN)

- **Feature importance analysis**

Since the RBF-based SVM model does not give direct feature weights, we performed a post-hoc permutation importance analysis to enhance its interpretability. Each feature in the validation set was individually randomly shuffled and then the resulting degradation in F1-score across the same 5-fold cross-valuation configuration observed. Correctness of Answer and Count of Attempts were the most important variables, as Table 5 shows; both

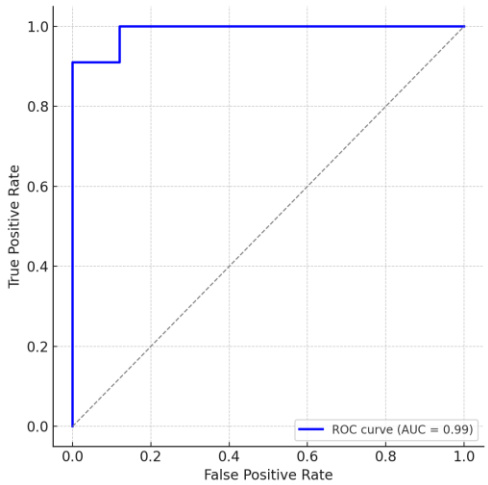


Figure 2: ROC Curve for SVM Model

greatly affect the performance of the model. These results confirm the behavioral presumptions driving our labeling approach. Response time had a modest impact; word difficulty had a smaller but detectable impact.

- **Cross validation and hyperparameter tuning**

Table 5: Permutation-based feature importance ranking

Feature	Mean Drop in F1-Score (%)	Relative Importance
Correctness of Answer	6.3%	High
Count of Attempts	5.0%	High
Response Time (sec)	3.7%	Moderate
Word Difficulty Level	2.4%	Low

These metrics collectively demonstrate to ensure generalizability; we used stratified 5-fold cross-validation during training. This preserved the class distribution in each fold, addressing potential imbalances in weakness labels (e.g., 60% "weakness" vs. 40% "no weakness").

For hyperparameter optimization:

- **Grid Search for hyperparameter tuning:**

Grid search was employed to systematically identify the optimal hyperparameters for the SVM model: the regularization parameter C and the kernel width γ (gamma) for the Radial Basis Function (RBF) kernel. The goal was to balance model complexity and generalization. A predefined set of values was tested for each parameter:

The regularization strength (C) was tested with values of 0.1, 1, 10, and 100. Lower C values (e.g., 0.10.1) emphasize a broader decision margin, allowing for increased training errors to mitigate overfitting. Higher

CC values (e.g., 100100) impose more stringent classification, aligning more closely with the training data.

Values evaluated were [0.001,0.01,0.1,1] for γ (RBF kernel effect radius). While greater γ values (e.g., 1) provide tightly fitting borders around data points, smaller γ values—e.g., 0.001—create more general, smoother decision boundaries.

Stratified 5-fold cross-validation was utilized to maintain class distribution, while the grid search evaluated combinations of C and γ to optimize the F1-score, a critical parameter for correcting class imbalance. The ideal configuration was C=10 and γ=0.1, yielding an F1-score of 88% on the validation dataset. This method adeptly matched accuracy, reducing false positives, and recall, reducing false negatives, thereby guaranteeing dependable diagnosis of student deficiencies without overfitting.

- **Kernel selection**

According to Table 6, three kernel types were tested to determine the best fit for modeling interactions between behavioral and linguistic features:

Table 6: Kernels comparison

Kernel	Avg. F1-Score	Standard Deviation
Linear	0.79	±0.03
Polynomial	0.83	±0.02
RBF	0.88	±0.01

i. **Linear Kernel:**
   - Assumes a linear relationship between features (e.g., direct proportionality between ResponseTime and Weakness).
   - Achieved 79% accuracy but failed to capture non-linear patterns (e.g., the combined effect of high AttemptsTimes and medium WordDifficulty).

ii. **Polynomial Kernel:**
   - Models' polynomial relationships (e.g., quadratic effects of #Attempts).
   - Tested with degree d=3 and coefficient r=0, achieving 83% accuracy. However, it was computationally expensive and prone to overfitting.

iii. **Radial Basis Function (RBF) Kernel:**
   - Outperformed others with 88% accuracy, excelling at detecting nuanced patterns like:
   - High AttemptsTimes + Incorrect Answer → Strong predictor of weakness.
   - Long ResponseTime + High WordDifficulty → Weakness only if Answer was incorrect.

The RBF kernel's flexibility in modeling localized patterns (e.g., clusters of students with similar behavioral traits) and its robustness to feature scaling made it ideal for the dataset. Unlike the polynomial kernel, RBF avoided overfitting while capturing interactions between features like Attempts Times and Word Difficulty, which were critical for identifying knowledge gaps.

- **Cross-validation performance**

The final model was validated using stratified 5-fold cross-validation as shown in table 7:

Table 7: Final SVM Model Cross-Validation Performance

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	88.7	85.9	90.8	88.3
2	89.2	86.5	91.4	88.7
3	88.1	85.2	90.4	87.7
4	88.8	86.3	90.7	87.4
5	89.5	88.35	91	89.66
Average	**88.86**	**86.45**	**90.86**	**88.35**

- **Final model setup**

The optimized SVM configuration was:

SVC (kernel='rbf', C=10, gamma=0.1, class_weight='balanced')

The metrics indicate a well-optimized model that effectively identifies vocabulary weaknesses with high precision and recall, while sustaining robust overall accuracy. The F1-score integrates these priorities, providing actionable insights for educators. A student who hesitates twice on a medium-difficulty word such as "İnşaat" (Work/Occupation) will be classified as "weak" with high confidence, prompting the provision of customized practice exercises. This performance confirms the SVM configuration (RBF kernel, C=10, γ=0.1) and the feature engineering strategy, which prioritized behavioral attributes such as Attempts and response time, in addition to linguistic factors like word difficulty.

2.9 Model integrating into learning system

Over the course of this phase, we included the model we had generated during the preparatory step into the system. As the student advances through each level and overcomes new problems, we will construct a new model and enhance the one that is already in place. After then, this updated model will be applied at the next and more advanced level. With this iterative approach, the data from the students' tests should be routinely updated. This will enable us to identify the areas of categorization where the learner lacks competence and thereafter enhance the activities in those spheres.

This stage of the methodology involves the integration and refinement of the Machine Learning (ML) model, focusing on enhancing its performance and adaptability following initial development and training. The objective is to incorporate the machine learning model into the broader system or workflow and enhance it

to improve accuracy, ensure robustness, and effectively manage a variety of real-world scenarios.

Upon integration of the model into the backend system, it is deployed for real-time predictions. In various scenarios, including game-based applications, the integration of the model as a REST API enables the gamification system to transmit input data and obtain predictions through HTTP requests. This facilitates efficient communication between the game interface and the machine learning model operating in the backend, ensuring seamless data flow and interaction.

In this final step, we are not concerned with the use of a specific system, and this system will not be discussed in this study. It may be any educational platform that utilizes a RESTful API to achieve the same objective deploying the trained model based on previously collected user behavioral data to identify weaknesses across word category classifications.

Refining an ML model starts with evaluating its performance using key metrics such as accuracy, precision, recall, and F1-score, as discussed previously. Understanding the model's strengths and limitations might help identify opportunities for development. Metrics can also be assessed for different subsets of data to determine if the model generalizes well or whether it performs poorly in certain contexts.

3 Discussion

With an accuracy of 89%, precision of 86%, recall of 91%, and an F1-score of 88%, the development and evaluation of the SVM-based model for spotting vocabulary shortcomings in Turkish language learners yielded quite impressive results. These measures highlight the resilience of the model and it's fit for systems of adaptive learning. More importantly, the addition of behavioral modeling, especially the integration of response time, number of attempts, and answer correctness significantly improved the predictive power of the model compared to conventional models that depend just on correctness.

Traditional vocabulary evaluation models typically treat learner performance as binary (correct vs. incorrect), which limits their capacity to detect uncertainty, hesitation, or overthinking behaviors that are pedagogically significant. In contrast, our behavioral modeling approach captured metacognitive indicators, allowing the model to recognize nuanced patterns such as students repeatedly hesitating on a moderately difficult word or taking excessive time to answer despite answering correctly. These behaviors were strong predictors of underlying weakness that binary-correctness models would miss. For example, the model successfully flagged students struggling with medium-difficulty terms like "İnşaat" based on both prolonged response times and multiple attempts an insight unattainable with traditional correctness-only metrics.

Moreover, in our permutation-based feature importance analysis, behavioral traits revealed great predictive value. Shuffling "correctness" and "number of attempts" resulted in the biggest F1-score drop, so attesting their indispensable importance. This shows that the decision-making process of the model gains orthogonal, non-redundant value from behavioral characteristics.

From a technical standpoint, the RBF kernel proved particularly effective for capturing these complex interactions. Empirical results showed that it outperformed linear and polynomial alternatives, achieving an F1-score of 88% with the lowest variance across cross-validation folds. Unlike linear kernels, which assume additive relationships among features, the RBF kernel models localized and non-linear patterns. This capacity was especially important in educational contexts where interactions between features such as how time spent, and correctness vary across word difficulty are rarely linear or independent. The polynomial kernel showed modest improvements over the linear kernel but suffered from overfitting and computational inefficiency. The RBF kernel struck the best balance between accuracy, generalization, and interpretability (with the aid of permutation-based feature analysis).

While this study focuses on Turkish vocabulary acquisition, the proposed framework holds potential for generalization across other languages and educational domains. The core components—behavioral data collection (e.g., response time, number of attempts), equation-based labeling, and SVM-based classification—are language-independent in structure and can be adapted to other linguistic contexts with appropriate adjustments to lexical difficulty metrics and thematic categorizations. Moreover, the methodology is domain-agnostic and can be extended beyond vocabulary learning to areas such as reading comprehension, grammar exercises, or even non-linguistic skill assessments, where learner behavior provides meaningful indicators of understanding or uncertainty. Future work could explore cross-linguistic validation by applying the framework to datasets in other languages or extend its use to interdisciplinary learning platforms where adaptive feedback based on learner behavior is critical for personalized instruction.

3.1 Limitations

Despite its advantages, the study has limitations. First and foremost, with 1,000 components in the collection (equivalent to 20 students), scalability becomes a question mark. The model worked well in our sample; however, its application to larger and more diverse groups such as youngsters or students learning several languages has not been evaluated.

Second, real-world apps may have different UI designs or network issues, so data collection assumptions, such as measuring attempts counts precisely, might not be applicable. For instance, if the interface is slow, it can make response times seem longer than they are, which would be misleading. Third, the study's focus on adults may limit its ability to generalize to younger groups, whose members may exhibit distinct characteristics (such as impulsivity or shorter attention spans.

Furthermore, introducing possible bias is the model relied solely on objective difficulty measures (e.g., syllabic complexity), and did not incorporate subjective

learner perceptions of difficulty, which may limit the personalization potential of the model. Future work should consider integrating real-time perceived difficulty feedback to complement phonetic classification. Linguistic specialists defined word difficulty; but subjective learner perceptions that is, a student finding "Ev" difficult because of personal experience—were not adequately recorded. Dynamic difficulty changes based on individual performance could be included in the next versions.

4 Conclusion

In summary, our approach shows that combining behavioral analytics and machine learning may effectively identify language learning deficits, providing a scalable solution for individualized education. It achieves the dual aims of efficient resource allocation and comprehensive student support by putting precision and recall first. Future work to improve data gathering procedures and expand validation cohorts will increase its usefulness, opening the path for more adaptable, responsive learning technologies.

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Appendix (A) Sensitivity Analysis of Weakness Score Equation (Eq. 1)

We performed a sensitivity analysis by varying the weights assigned to the behavioral and linguistic parameters: correctness of the answer (wCorrect), response time (wTime), hesitation count (wAttempts), and word difficulty (wDifficulty), so validating the robustness and statistical grounding of the rule-based weakness score equation (Equation1). The objective was to investigate how these weights affected SVM model downstream classification performance.

Each weight was varied within a range of ±10%, ±20%, and ±30% relative to its baseline configuration (wCorrect = 0.4, wTime = 0.2, wAttempts = 0.3, wDifficulty = 0.1), while ensuring that the total sum of weights remained equal to 1. The corresponding weakness labels were recalculated for each configuration and used to train separate SVM classifiers.

Stratified 5-fold cross-valuation was used in evaluation of the models. The results showed that only modest weight fluctuations would cause just slight changes in model performance. As Table A.1 shows, the F1-scores stayed within a limited band of ±2% from the

Table A.1: Weight Variations on SVM F1-Score

Weight Configuration (wCorrect, wTime, wAttempts**, wDifficulty)**	**F1-Score (%)**
(0.4, 0.2, 0.3, 0.1) [Baseline]	88.0
(0.5, 0.15, 0.25, 0.1)	87.5
(0.3, 0.25, 0.35, 0.1)	88.1
(0.4, 0.3, 0.2, 0.1)	87.6
(0.35, 0.25, 0.3, 0.1)	87.9

baseline. Especially, the classification performance was more sensitive to variations in wCorrect and wAttempts, so verifying their major contribution in pointing up learning shortcomings.

These findings imply that, despite empirical construction, the rule-based equation shows enough stability and predictive dependability over a spectrum of weight settings. This justifies its use as a workable pre-labeling system in situations where ground truth labeled by humans is not available.

Appendix (B) Bootstrap Resampling for Robustness Evaluation

By using 100 iterations of bootstrapping resampling to assess the SVM model's stability and resilience despite a small dataset. Training data was sampled with replacement from the original 1,000 interactions in every iteration; the SVM model (RBF kernel, C=10, γ=0.1) was trained and tested using stratified 5-fold cross-validation.

The results, summarized in Table B.1, show consistently high performance across bootstrap samples. The F1-score averaged 88.2%, with a standard deviation of ±1.6, confirming the model's resilience to training data variability and supporting its applicability even under small sample regimes.

This procedure strengthens the statistical credibility of our findings and demonstrates that the proposed system maintains its effectiveness across data permutations.

Table B.1: SVM Model Performance Across 100 Bootstrap Resampling Iterations

Metric	**Mean (%)**	**Std. Dev. (%)**	**Min (%)**	**Max (%)**
Accuracy	88.9	±1.5	85.4	91.3
Precision	86.4	±1.8	82.6	89.7
Recall	90.5	±1.3	87.3	92.6
F1-Score	88.2	±1.6	85.0	90.8

Appendix C – Implementation and Reproducibility Guidelines Using PHP-ML

We provide below a thorough description of the preprocessing and model training pipeline applied using the PHP-ML library to support reproducibility and help adoption of methodology in related educational technology research. These processes are meant to guarantee constant performance and replicability in several surroundings.

1. Data Preprocessing Workflow

The raw dataset consisted of behavioral and linguistic features, which underwent the following transformation steps prior to model training:

- **Categorical Encoding:**
  - Word Classification: Each thematic category (e.g., Education, Family) was mapped to a unique integer.
  - Answer Encoding: Correct answers were encoded as 1, and incorrect as 0.
  - Difficulty Level: Difficulty categories were numerically mapped as Easy = 1, Medium = 2, Hard = 3.
- **Numerical Feature Handling:**

Retained as constant values are response time and attempts count. Min-Max Scaling brought all numerical features into the [0, 1] range to guarantee fit with SVM kernel behavior.

2. Support Vector Machine Configuration

Model training was carried out using the Support Vector Classification (SVC) class provided in PHP-ML. Key configuration details are as follows:

- **Library Version:** PHP-ML v0.10+
- **PHP Version:** >= 7.1
- **Classifier:** Phpml\Classification\SVC
- **Kernel Type:** Radial Basis Function (RBF)
- **Class Weighting:** Balanced, to account for mild class imbalance (weak vs. non-weak labels)
- **Features Used:** Encoded class, difficulty, response time, correctness, and number of attempts

3. Hyperparameter Optimization (Grid Search)

To optimize model performance and reduce overfitting, we employed a grid search approach over the following hyperparameter ranges mentioned in Table C.1.

Table C.1: C and Gama search values

Parameter	Tested Values
C	0.1, 1, 10, 100
gamma	0.001, 0.01, 0.1, 1

- Each parameter combination was evaluated using stratified 5-fold cross-validation.
- The F1-score was used as the primary evaluation metric to ensure balanced consideration of precision and recall.

The optimal configuration selected was C = 10, gamma = 0.1, yielding the highest cross-validated F1-score.

4. Pseudo-Code for Reproduction Using PHP-ML

The following pseudo-code outlines the key steps in training the SVM model:

```
use Phpml\Classification\SVC;
use Phpml\SupportVectorMachine\Kernel;
use Phpml\CrossValidation\StratifiedRandomSplit;
use Phpml\ModelManager;

// Step 1: Prepare input data
$X = [...]; // Feature vectors (normalized)
$y = [...]; // Labels (0 = no weakness, 1 = weakness)

// Step 2: Initialize classifier
$classifier = new SVC(
   Kernel::RBF,   // Kernel type
   $cost = 10,    // Regularization parameter C
   $gamma = 0.1,  // RBF kernel width
   $enableProbabilityEstimates = true
);

// Step 3: Train the model
$classifier->train($X, $y);

// Step 4 (optional): Save the trained model
$modelManager = new ModelManager();
$modelManager->saveToFile($classifier, 'svm_model.phpml');
```

A Hard Voting Ensemble Model of the Logistic Regression, Support Vector Machine and Random Forest for Network Intrusion Detection

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Keywords: SVM, ensemble, logistic regression, random forest, intrusion, hard voting, intrusion, web packets, hybrid model, misprediction

Received: March 11, 2025

The rapid evolving landscape of cybersecurity, the need for robust and efficient intrusion detection systems (IDS) has never been more critical. The real-time network traffic environments are plagued with the challenges posed by traffic routing and complex network behaviours. To this end, this paper proposes four hybrid/ensemble models for the detection of intrusion across complex networks infrastructures by combining logistic regression (LR) and support vector machines (SVM), and random forest (RF). The paper leverages the hard voting ensemble strategy to mix the interpretability of LR; fusing decision capacity of RF; and classification efficacy of SVM, to enhance detection accuracy and reduce false positive rates. During the experimentation of the proposed ensemble models, the two standard datasets were acquired, that is, the KDD Cup 1999 and CSE-CIC-IDS2018, for the training and testing phases after the ENN-SMOTE method data resampling strategies. The results showed that, the resampled binary-class dataset (KDD Cup 1999), the SVM-RF obtains best accuracy of 99.42%. The biggest precision score of 99.94% was computed for the LR-RF model. The recall measure of 99.01% was attained by the SVM-LR-RF model. F1-score of 99.37% was observed for the SVM-RF model. Similarly, upon ENN-SMOTE method resampling of the multi-class dataset (CSE-CIC-IDS2018), accuracy of 92.06% achieved by the SVM-RF model. The precision of 99.68% was witnessed for the SVM-RF. With the recall score, the SVM-LR-RF model offers the widest margin of 90.76%. The F1-score of 94.73% was recorded for the SVM-LR-RF model. The Asymptotic Significance (2-sided test) of 0.043 is less than p-value at the significance level of 5%. The paper established that, the ensembles models performances with the ENN-SMOTE technique were more significant than the RFE for data preprocessing.

Povzetrek: Prispevek predstavi ansambelski model s trdim glasovanjem, ki združuje logistično regresijo, podporne vektorske stroje in naključni gozd za izboljšano zaznavo vdorov v omrežjih.

1 Introduction

Organizations attempt to address cyber-attacks by removing suspicious activity, threats and risks across network infrastructures [1]. It became commonplace to adopt specialized software defense techniques to keep-up with network data scrutiny [2]. The fresh security threats coupled with enormous traffic transmitted across wireless networks continue to pose new necessities for the machine learning-associated solutions from the standpoints of the physical and functional differences, especially from the network topology and device meta data of numerous computing devices [3]. The use of intrusion detection systems (IDS) is common, though less-effective in case of anomaly or signature-affiliated IDS, which utilizes deep learning and machine learning algorithms to improve performance [4].

There are main weaknesses include: high false alarm, use of predefined threats and attacks, and relatively controlled detection operations. Intrusion prevention system (IPS) performs intrusion-repelling tasks for network and computer system by leveraging on IDS' log files [5]. IPS takes necessary actions upon identifying packet dropping activities and unauthorized addresses. Both approaches are emboldened by certain levels of intelligence for recognizing and classifying abnormal behaviours of network packets [6]. Machine learning and deep learning algorithms play serious functions in providing improved intelligences for the IDS and IPSs during detection and rerouting operations on networks.

In recent time, IDS combines hybrid models, algorithms or approaches with the goal of maximizing their respective advantages and reducing their disadvantages. Hybrid models improve detection accuracy and resilience against different kinds of cyber threats by integrating, for instance, machine learning algorithms with statistical techniques or heuristic approaches. This dual or multifaceted strategy can result in more complete security solutions and improve adaptation to changing attack patterns [7]. The value of hybrid models resides in their capacity to overcome the drawbacks of conventional

single-algorithm systems, which may find it difficult to handle intricate or unusual threats.
In [8], the authors had demonstrated that hybrid approaches not only yield greater detection rates but dramatically reduce false positive rates, which are crucial in preserving the reliability of intrusion detection systems.

The author in [9] revealed that, hybrid models perform better in terms of accuracy and detection rates as well as greater generalization across various datasets like pcap.

The main objectives of this paper include:

- To preproess and optimize binaey-class and multi-class network intrusion datasets from the Kaggle standard repositories using ENN-SMOTE technique.
- To develop four hybrid models for the intrusion traffic detection across wireless networks based on SVM, RF, and LR algorithms using hard voting technique.
- To evaluate the effectiveness of the ensemble models with ENN-SMOTE and Recursive Feature Selection using measures like accuracy, precision, recall, F1-score, confusion matrix, type I error and type II error.

2 Related works

In [10], the authors developed a hybrid Adaptive Ensemble for Intrusion Detection (HAEnID) comprising Stacking Ensemble (SEM), a Bayesian Model Averaging (BMA), and a Conditional Ensemble method (CEM). Using the CIC-IDS 2017, the HAEnID achieved accuracy of 97 to 98%. Further feature selection raises the accuracy to 98.79% for the BMA-M (20). There is the need to lower false alarm rates and increase the reliability especially for multi-class dataset than binary-class.
Sayem et al. [11] proposed an ensemble model comprising the base learner and the meta-learner. The base learner had convolutional neural networks, long short-term memory, and gated recurrent units, and the meta-learner had a deep neural network model. UNSW-15 and CICIDS-2017 datasets were used for validation, which gave accuracy of 90.6% and 99.6% and an F1-score of 90.5% and 99.6% accordingly. More complex features and multi-class dataset can be utilized to test the model.
In 2024, Saheed and Misra [12] developed an ensemble of wolf optimizer (GWO) with a decision tree, random forest, K-nearest neighbor, and multilayer perceptron for intrusion classification tasks. UNSW-NB15, BoT-IoT were used for training and testing, which offered accuracy of 100% for GWO, and 99.9% for DR, Precision of 99.59%, ROC of 99.40%, and False Alarm Rate of 1.5. Future to sample more complex and multi-class datasets.
In 2025, Almania et al. evolved AIDS model composed of Fuzzy c-means clustering, K-Nearest Neighbors (KNN), and weight mapping. The imbalanced datasets issues were overcome with ensemble classifiers Random Forest (RF) and Decision Tree (DT). Network traffic data (DoS, R22, U2R) were curated for the analysis. The AIDS offered accuracy of 97.7% and a false alarm rate of 2.0%. Though, detection rate can be pursued in the future works. Again, the computational complexity and data imbalanced must be handled while more adaptive models can be explored for real-world applications [13].
In [14], the authors introduced stack classifier model for improving the classification of intrusions in IoT datasets. The K-Best feature selection algorithm and ensemble modelling were combined in optimizing essential classification metrics through combination of strengths of the single machine learning models. The Ton IoT dataset was used for validation which provides accuracy of 99.99%, recall of 99.99%, F1-score of 99.98%, and low false positive rates. But, there is the need to consider the different threat types, and network infrastructures.
In 2024, Jemili et al. hybridized Random Forest (RF), XGBoost, and decision trees (DT) for intrusion detection in big data. The model was validated with N-BaIoT, NSL-KDD, and CICIDS2017. The model results attained accuracy of 97% by capitalizing on the consensus of diverse classifiers. There is need to raise the level detection rate for emerging threats [15].
In 2023, Hnamte and Hussain were motivated by deep learning's exceptional performance in various detection and identification tasks by presenting an intelligent and efficient network intrusion detection system (NIDS) based on DL for attack detection. The hybrid of CNN and LSTM model was trained with real-time traffic datasets namely; CICIDS2018 and Edge_IIoT. The performance of the model using multiclass classification achieved a 100% and 99.64% accuracy rates respectively when trained and tested with the datasets. The ensemble model had better performance than single model despite its extended runtime [16].
A hybrid model of convolutional neural network and bidirectional long short-term memory was advanced by Bowen et al. [17] to improve the malicious traffic recognition. Authors validated the proposed model using for CIC-IDS2017, IoT-23 in which accuracy of 98.00% and 99.00% were attained with multi-class and binary-class datasets. However, there is the need to explore more classifiers.
In 2023, Almarshdi et al. combined the convolutional neural network and bidirectional long short-term memory models for inspecting the intrusion traffic inside the UNSW-NB15 dataset. The imbalance in the data was resolved with a synthetic data generation technique. The outcomes revealed that, the hybrid model obtained accuracy of 92.10%. More threats types can be investigated in the future work [18].
The hybrid model of the convolutional neural network and long short-term memory algorithm was implemented by Yassen et al. [19] for multi-class detection tasks such as network intrusion based on secondary datasets (CICID2018 and Edge_IIoT). After training and testing phases, the hybrid model realized accuracy of 100% and 99.64%. However, the ensemble models and local dataset could be implemented subsequently.

The convolutional neural network and GRU algorithms were hybridized to reinforce the performance for intrusion detection in CICIDS-2017 dataset [20]. The results revealed that, the hybrid model produced accuracy of 98.73% and false positive rate of 0.075. Nevertheless, the performance of the hybrid can be tested with complex datasets to measure the accuracy, false alarm, and time elapsed in local settings.

In 2023, Alomari et al. proposed a hybrid algorithm of dense and long short-term memory algorithms for investigating the malware intrusion traffic using dissimilar feature generation strategies. The first case reduced features further by 42.42% from the initial 18.18%, which gave rise to accuracy of 5.84% with tradeoff of 0.07%. The other case minimized the features by 93.50% from the original 81.77%, which realized accuracy of 9.44% with tradeoff of 3.79%. Though, more forms of network intrusion traffic datasets could be included in later studies [21].

The performances of the long short-term memory and GRU model were mixed to from a hybrid model for intrusion detection in Internet of Things networks by [3]. The Harris Hawk optimization and fractional derivative mutation were applied to IoT-23 and ME-WMVEDL datasets for the feature selections. The outcomes indicated that, the hybrid model attained accuracy of 98.125 and 97.34%. More so, the proposed model realized AUC-ROC of 0.9982 and 0.9994 respectively. Though, the class imbalance resampling of dataset was not performed.

Gohari et al. hybridized convolutional neural network and long short-term memory algorithms to detect network traffic using CICAndMal2017. The hybrid classifier eliminates preprocessing data stage which speedups the binary classification tasks. The outcomes showed that, the detection accuracy of 97.79% for binary data, 98.90% for category, and 98.90% for others. It demonstrates the superiority of hybrid models for intrusion detection tasks. More complex data features could be investigated in future [22].

The summary of the related studies reviewed including authors, objectives, methodology, datasets, results and weaknesses as presented in Table 1.

Table 1: Summary of related studies.

Authors	**Objectives**	**Methodology**	**Datasets**	**Results**	**Weaknesses**
Bowen et al. (2023)	Network traffic classification.	Hybrid model of convolutional neural network and bidirectional long short-term memory.	CIC-IDS2017, IoT-23	Accuracy: 98.00%, 99.00%	More classifiers can be investigated.
Almarshdi et al. (2023)	Intrusion traffic inspection.	Hybrid of Convolutional neural network and bidirectional long short-term memory models.	UNSW-NB15	Accuracy: 92.10%	Binary dataset only.
Yassen et al. (2023)	Network intrusion detection.	Hybrid of the convolutional neural network and long short-term memory algorithms.	CICID2018 and Edge_IIoT	Accuracy: 100%, 99.64%.	Multi-class dataset only.
Henry et al. (2023)	Network intrusion detection.	Hybrid of convolutional neural network and GRU algorithms.	CICIDS-2017	Accuracy: 98.73% False positive rate: 0.075	Less complex dataset.
Alomari et al. (2023)	Malware intrusion traffic detection.	Hybrid of dense and long short-term memory algorithms with features reduction.	Malware	Accuracy: 9.44% with tradeoff of 3.79%.	Low datasets features.
Sanju (2023)	IoT intrusion detection.	Hybrid of long short-term memory and GRU model with features selection based on Harris Hawk optimization and fractional derivative mutation.	IoT-23 and ME-WMVEDL	Accuracy: 98.125, 97.34%. AUC-ROC: 0.9982, 0.9994.	Class imbalance resampling not performed.

Gohari et al. (2021)	Network traffic detection.	Hybrid of convolutional neural network and long short-term memory algorithms.	CICAndMal2017	Accuracy: 97.79% - binary data. 98.90% - category data 98.90% - others.	Less complex dataset utilized.
Ahmed et al. (2024)	Intrusion detection	novel Hybrid Adaptive Ensemble: Bayesian Model Averaging, Stacking Ensemble, Conditional Ensemble method.	CIC-IDS 2017	Accuracy: 97-98%. Feature selection: 98.79%.	High false alarm and low detection rate.
Sayem et al. (2024)	Network intrusion detection.	Base learner: Convolutional neural networks, long short-term memory, and gated recurrent units, The meta-learner: deep neural network model	UNSW-15 and CICIDS-2017	Accuracy: 90.6% and 99.6%. F1-score: 90.5% and 99.6%.	Few performance metrics and less complex datasets utilised.
Almotairi et al. (2024)	IoT Intrusion detection.	Stack classifier.	Ton IoT.	Accuracy: 99.99%. Recall: 99.99%, F1-score: 99.98%	Limited threats data.
Saheed & Misra (2024)	IoT intrusion detection.	Ensemble of wolf optimizer (GWO) with a decision tree, random forest, K-nearest neighbor, and multilayer perceptron.	UNSW-NB15, BoT-IoT.	Accuracy - GWO: 100%, DR: 99.9%, Precision: 99.59%, ROC: 99.40%, and FAR: 1.5	Limited multi-class dataset.
Almania et al. (2025)	Network intrusion detection.	AIDS model composed of Fuzzy c-means clustering, K-Nearest Neighbors (KNN), and weight mapping. Data class imbalance with Random Forest (RF) and Decision Tree (DT).	Network traffic: DoS, R22, U2R	Accuracy: 97.7%, False alarm rate: 2.0%.	High computational complexity, data imbalance and low detection rate.
Jemili et al. (2024)	Intrusion detection in big data.	Hybrid of RF, XGBoost, and DT.	N-BaIoT, NSL-KDD, CICIDS2017	Accuracy: 97%	Low detection rate.
Hnamte and Hussain (2023)	Network intrusion detection.	hybrid of CNN and LSTM.	CICIDS2018, Edge_IIoT.	Accuracy: 100% and 99.64%.	Extended runtime.
This paper	Network intrusion detection.	Ensemble models of SVM- RF, SVM- LR, LR-RF, and SVM-LR+RF.	KDD CUP 1999, CSE-CIC-IDS2018.	Accuracy, Precision, F1-Score, Recall, confusion matrix,	Ensemble strategy of hard voting only.

		ENN-SMOTE data preprocessing strategy for binary and multi-class datasets.		AUC-ROC and runtime complexity measured.	

3 Research methodology

The paper attempts to enhance the wants to investigate the following research questions to achieve the objectives set:

i. What are the implications of applying ENN-SMOTE technique on binary-class and multi-class datasets 'accuracy and false positive rates?
ii. Do hybrid models for the intrusion traffic detection across wireless networks for binary-class datasets outperform multi-class datasets after addressing imbalance problems?
iii. Do ensembles model fit into real-world intrusion traffic detection across networks?

Consequently, this study proposes the hybrid strategy to leverage on the advantages of the LR, RF, and SVM based on hard voting strategies in building the ensemble models of RF+SVM, LR+SVM, and LR+RF+SVM. This model aims to improve intrusion detection accuracy by preprocessing the data with ENN-SMOTE technique and fusing the strong classification skills of SVM with the probabilistic insights of LR, and multiple-decision trees of RF as shown in Figure 1.

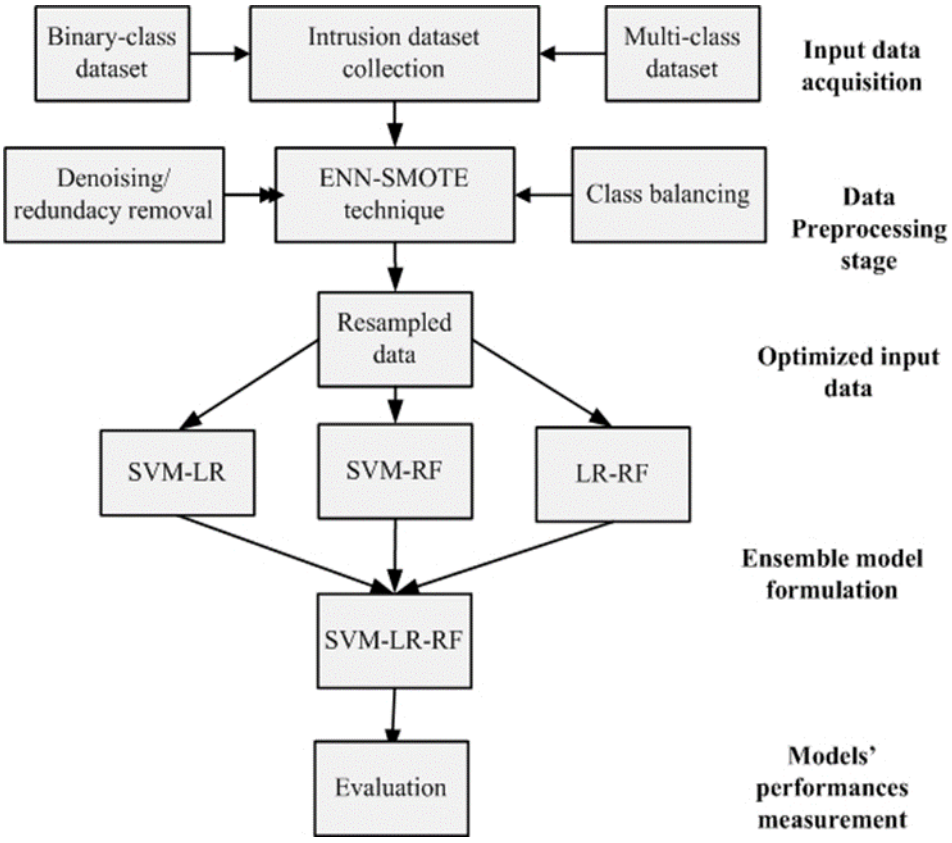


Figure 1. The proposed hybrid models for the network intrusion detection.

From Figure 1, the input data acquisition receives the intrusion datasets from the binary-class and multi-class, which contain begnin and different attacks monitored and logged on the standard repository. The second stage is the data preprocessing to remove noise and redistribute the class-make up in order to address the undersampling or oversampling problems for classifiiers. The ENN-SMOTE resampling technique was adopted for this study. The resampled data is the optimized input data to the proposed ensemble/hybrid models. The study investigates the hybrid models performances with the optimized datasets to determine the influences on the following: SVM-LR, SVM-RF, LR-RF, and SVM-LR-RF. The final stage is the models' performance measurement using standard metrics like accuracy, precision, recall, F1-score, confusion matrix and runtime. The outcomes are used to determine the best classifiers to be implemented in intrusion detection system of enterprises and organization in terms of speed and effectiveness.

Data Collection: The first of the secondary dataset was collected from Kaggle monitored on Wireshark tool. KDD CUP 1999 comprises 41 quantitative and qualitative features of normal and attack data (3 qualitative and 38 quantitative features). The class variable is Normal and Anomalous categories of traffic data for a wide variety of intrusions created in a military network setup. The network intrusion detection is composed of 22544 rows and 41 columns for the Test_data.csv file, and 25192 rows and 42 columns for the Train_data.csv.

The second dataset is made up of 36417 rows and 13columns of URLs from begnin and malicious websites. The URL dataset known as CSE-CIC-IDS2018 contains 7311 of phishing attacks, 7776 of benign, 7930 of Defacement, 6707 of malware attacks, and 6693 of spam attacks from the InfogramALL.csv file.

Data preprocessing: Data cleaning is the foundational step in preparing the dataset for analysis, which involves conversion of the categorical features and removal of the irrelavant features. The StandardScalar () was applied for scaling the features. The scalar.fit () and scalar. transform () were applied on the numeric features to prepare for modeling purposes. This ensures that the dataset remains as complete as possible while minimizing the risk of skewed analysis.

The class imbalance solution was addressed using ENN-SMOTE technique to reduce the dimensionality and noise in both datasets. The dataset dimension before and after the class balancing as follows:

KDD CUP 1999: The original dataset sample class count: int64(1): 13449, int64(0): 11743. Also, the resampled dataset sample class count: int64(1): 13332, int64(0): 13322. The class distributions for the original dataset and the ENN-SMOTE method resampled class distribution are given in Table 2.

Table 2: The outcomes of the ENN-SMOTE technique on KDD CUP 1999.

Class	**Count (Before ENN-SMOTE)**	**Class**	**Count (After ENN-SMOTE)**
Normal	13449	Normal	13332
anomaly	11743	anomaly	13322

Figure 2 shows the graphical representations of the class distributions before and after ENN-SMOTE method's operation on the KDD CUP 1999 dataset, which improvement in the eventual class distribution and noise reduction.

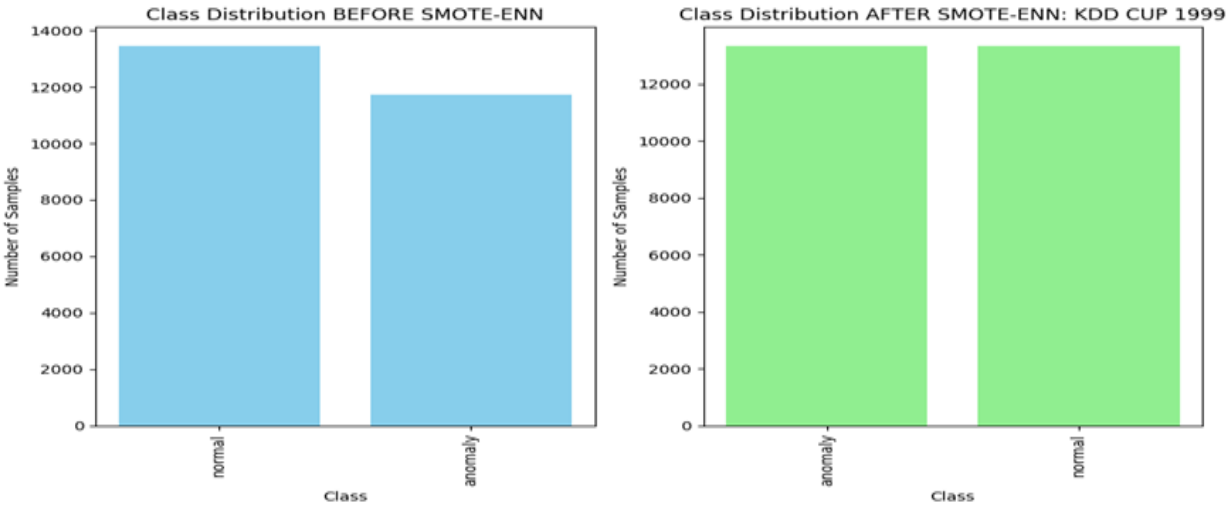


Figure 2: The class distribution for the ENN-SMOTE technique applied on KDD CUP 1999 dataset.

CSE-CIC-IDS2018: The orignal dataset sample class count: int64(0): 7930, int64(1): 7776, int64(3): 7311, int64(2): 6707, int64(4): 6693. Moreso, the resmapled dataset sample class count: int64(4): 7536, int64(2): 7524, int64(0): 7300, int64(1): 7180, int64(3): 5637. The class distributions for the original dataset and the ENN-SMOTE method resampled class distribution are given in Table 3.

Table 3: The outcomes of the ENN-SMOTE technique on CSE-CIC-IDS2018.

Class	**Count (Before ENN-SMOTE)**	**Class**	**Count (After ENN-SMOTE)**
Defacement	7930	Defacement	7300
Benign	7776	Benign	7180
Phishing	7311	Phishing	7524
malware	6707	malware	5637
Spam	6693	Spam	7536

Figure 3 shows the graphical representations of the class distributions before and after ENN-SMOTE method's operation on the CSE-CIC-IDS2018 dataset, which advancement across the multi-class eventual class with minimized noise.

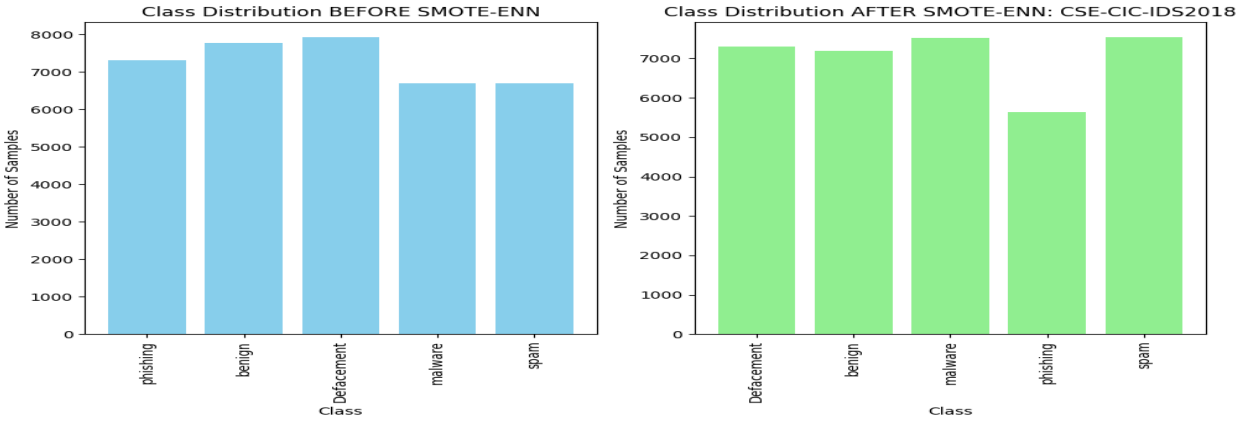


Figure 3: The class distribution for the ENN-SMOTE technique applied on CSE-CIC-IDS2018 dataset.

Programming Language: Python 3.8 or above on Google Colaboratory environment.
Machine Learning Libraries: Scikit-learn, imblearn, time, TensorFlow/PyTorch.
Data Processing Tools: Pandas and NumPy for data manipulation, SciPy for statistical computations.
Visualization Tools: Matplotlib and Seaborn for plotting data and model performance metrics.
Stream Processing Tools: Apache Kafka or Apache Flink for real-time network traffic analysis.
Data format: Microsoft Excel CSV for storing captured traffic logs and network packets.
Hyperparameters setting of the base classifiers:
Support Vector Machine (SVM): kernel = rbf, probability = False, random state=42.
Logistic Regression (LR) = maximum number of iteration =1000, random state=42.
Random Forest Classifier (RF): number of estimators =100, random state=42.
Performance Evaluation Metrics: The hybrid models' performances were assessed using various evaluation metrics, including and runtime, to ensure that it effectively distinguishes between normal and intrusive traffic. The key metrics used in the evaluation process:
Accuracy measures the percentage of correctly classified instances (both normal and malicious traffic) out of the total instances.
Precision evaluates how many of the detected intrusions were actual attacks.
Higher precision means fewer false positives.
Recall (or sensitivity) measures how well the model detects actual intrusions among all instances of intrusion. A high recall indicates the model is good at detecting intrusions but might produce more false positives.
F1 Score is the harmonic mean of precision and recall, providing a balanced metric when the dataset has imbalanced classes.
Area under curve (AOC ROC) is the measures the effectiveness of classification models on binary-class or multi-class datasets.
Confusion matrix provides a comprehensive view of the model's performance, showing the number of true positives, true negatives, false positives, and false negatives.
Runtime measure the time taken to perform model training and validation in seconds of the CPU clock.
The comparisons of the proposed ensemble models outcomes after preprocessing of dataset with ENN-SMOTE class imbalance technique against the optimal features within the dataset based Recursive Features Selection (RFE) techniques. The Related Samples Wilcoxon Signed Rank Test used to measure the significance of the outcomes attained by this study.

4 Results and discussion

Cyber-threats continue to evolve in complexity and frequency; organizations face significant challenges in protecting their networks from malicious activities. Traditional security measures often fall short in detecting sophisticated attacks, leading to severe data breaches and financial losses. This paper attempts to provide an effective network intrusion detection system (NIDS) for enterprises, which is capable of identifying both normal and abnormal network traffic, allowing for timely responses to potential threats. The primary challenge lies in developing a machine learning-based models such as SVM-LR, SVM-RF, LR-RF, and SVM-LR-RF ensemble models. Two resampled binary-class and multi-class network intrusion datasets whose classification performances scores are presented in the proceeding subsections.

4.1 Support vector machine and logistic regression ensemble model

Table 4 presents the outcomes of the SVM+LR ensemble model for the detection of intrusion traffic composed of binary-class and multi-class acquired the Kaggle data repository. The performance of SVM+LR ensemble model measured with accuracy, precision, recall, F1-score, AUC ROC and confusion matrices for the both datasets.

Table 4: The outcomes of the SVM+LR Ensemble model.

Dataset	Accuracy	Precision	Recall	F1-score	AUC ROC	Confusion matrix
KDD Cup 1999	0.9803	0.9890	0.9685	0.9786	0.9795	[[3997 38] [111 3412]]
CSE-CIC-IDS2018	0.8556	0.9906	0.8242	0.8998	0.89.77	[[2266 67] [1511 7082]]

From Table 4, the SVM+LR ensemble model with ENN-SMOTE resampled KDD Cup 1999 was best for accuracy of 98.03%, recall of 96.85%, F1-score of 97.86% against the resampled CSE-CIC-IDS2018 data, which performed well for precision of 99.06%. These outcomes can be attributed to denoising and class-balancing undertaken by the study. Moreso, the SVM-LR model's performance with type I error of 2.70% and type II error of 1.10% are acceptable for the missing on the positive and negative for the KDD Cup 1999 dataset. Whereas the SVM-LR model achieved type I error of 40.00% and type II error of 0.94% as acceptable for misprediction of the positive and negative classes (acceptable) in the CSE-CIC-IDS2018 dataset. Therefore, the research question can be answered in the affective as ENN-EMOTE improved and optimized the datasets.

4.2 Support vector machine and random forest ensemble model

Table 5 presents the outcomes of the SVM-RF ensemble model for the detection of intrusion traffic comprising of acquired binary-class and multi-class datasets from the Kaggle. The performance of SVM+LR ensemble model measured with accuracy, precision, recall, F1-score, AUC ROC and confusion matrices for the both datasets.

Table 5: The outcomes of the SVM+RF Ensemble model.

Dataset	Accuracy	Precision	Recall	F1-score	AUC ROC	Confusion matrix
KDD Cup 1999	0.9942	0.9991	0.9884	0.9937	0.9937	[[4032 3] [41 3482]]
CSE-CIC-IDS2018	0.9141	0.99681	0.8936	0.9424	0.9415	[[2308 25] [914 7679]]

From Table 5, the SVM+RF ensemble model with ENN-SMOTE resampled KDD Cup 1999 offered the highest accuracy of 99.42%, precision of 99.91, recall of 98.84%, F1-score of 99.37%, and overtook the outcomes with the resampled CSE-CIC-IDS2018 data. These outcomes can be attributed to denoising and class-balancing as most suitable for the binary-class data. The SVM-RF model generated the type I error of 1.00% and type II error of 0.09% as mispredictions for the positive class and negative class (acceptable) in the KDD Cup 1999 dataset. Similarly, the SVM-RF model scored the type I error of 28.37% and type II error of 0.32% as the mispredictions of the positive class (unacceptable) and negative class (acceptable) in the CSE-CIC-IDS2018 dataset. Therefore, this answers the research question that the ENN-EMOTE technique improved and optimized the dataset for high performance of the model.

4.3 Logistic regression and random forest ensemble model

Table 6 presents the outcomes of the LR-RF ensemble model for the detection of intrusion traffic comprising of acquired binary-class and multi-class datasets available at the Kaggle. The performance o LR-RF ensemble model measured with accuracy, precision, recall, F1-score, AUC ROC and confusion matrices for the both datasets.

Table 6. The outcomes of the LR+RF Ensemble model

Dataset	Accuracy	Precision	Recall	F1-score	AUC ROC	Confusion matrix
KDD Cup 1999	0.9843	0.9994	0.9668	0.9828	0.9831	[[4033 2] [117 3406]]
CSE-CIC-IDS2018	0.8688	0.9967	0.8360	0.9093	0.9129	[[2309 24] [1409 7184]]

From Table 6, the LR+RF ensemble model with ENN-SMOTE resampled KDD Cup 1999 offered the highest accuracy of 98.43%, precision of 99.94, recall of 96.68%, F1-score of 98.28%, and then trailed by the outcomes from the resampled CSE-CIC-IDS2018 data. These outcomes can be attributed to denoising and class-balancing was highly effective for the binary-class data during the model validation. The LR-RF model generated the type I error of 0.87% and type II error of 1.12% as mispredictions for the positive class and negative class (acceptable) in the KDD Cup 1999 dataset. Similarly, the LR-RF model scored the type I error of 26.01% and type II error of 0.94% as mispredictions of the positive class (unacceptable) and negative class (acceptable) in the CSE-CIC-IDS2018 dataset. Therefore, the answer to the research question is the ENN-EMOTE technique improved and optimized the dataset for both binary-class and multi-class classification tasks of the LR-RF ensemble model.

4.4 The proposed ensemble model

Table 7 shows the outcomes of the SVM-LR-RF ensemble model validated with the detection of intrusion traffic datasets acquired the Kaggle. The performance of SVM-LR-RF ensemble model measured with accuracy, precision, recall, F1-score, AUC ROC and confusion matrices for both binary-class and multi-class datasets.

Table 7: The outcomes of the SVM-LR-RF ensemble model.

Dataset	Accuracy	Precision	Recall	F1-score	AUC ROC	Confusion matrix
KDD Cup 1999	0.9902	0.9889	0.9901	0.9895	0.9902	[[3996 39] [35 3488]]
CSE-CIC-IDS2018	0.9206	0.9906	0.9076	0.9473	0.9379	[[2259 74] [794 7799]]

From Table 7, the proposed ensemble model validated using the ENN-SMOTE resampled KDD Cup 1999 offered the largest accuracy of 99.02%, recall of 99.01%, F1-score of 98.95%, and then trailed by the outcomes from the resampled CSE-CIC-IDS2018 data except for precision of 99.06%. The outcomes are possible due the denoising and class-balancing processes offered ENN-SMOTE method during preprocessing phase. Also, the binary-class data are best fitted for proposed ensemble model. The SVM-LR-RF model generated the type I error of 0.87% and type II error of 1.12% as mispredictions for the positive class and negative class (acceptable) in the KDD Cup 1999 dataset. Similarly, the SVM-LR-RF model scored the type I error of 26.01% and type II error of 0.94% as mispredictions of the positive class (unacceptable) and negative class (acceptable) in the CSE-CIC-IDS2018 dataset. The answer to the research question is that the ENN-EMOTE technique improved and optimized the dataset when applied at preprocessing phase in either case of dataset.

4.5 Models' validation performances compared

The models were trained and tested with 70% and 30% portions of the original intrusion datasets acquired from KDD Cup 1999 and CSE-CIC-IDS2018 available at the Kaggle. The prediction outcomes of the various hybrid models and mispredictions errors for intrusion detection are given in Table 8.

Table 8: Summary of the ensemble models' performances with KDD Cup 1999 dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)	Type I Error (%)	Type Error II (%)	Runtime (s)
Without ENN-SMOTE technique								
SVM+LR+ RF	99.17	99.15	99.06	99.11	99.16	0.82	0.85	9.89
SVM + RF	99.43	99.89	98.89	99.39	99.40	0.96	0.11	7.75
SVM + LR	97.75	99.15	96.00	97.55	97.64	0.35	0.85	10.15
LR + RF	98.12	99.91	96.05	97.95	97.99	3.33	0.09	4.90
With ENN-SMOTE technique								
SVM + LR + RF	99.02	98.89	99.01	98.95	99.02	0.89	1.11	8.93
SVM + RF	99.42	99.91	98.84	99.37	99.37	1.01	0.09	5.99
SVM + LR	98.03	98.90	96.85	97.86	97.95	2.70	1.10	8.07
LR + RF	98.43	99.94	96.68	98.28	98.31	2.82	0.06	2.83

The results in Table 8 indicated that, focusing on the binary-class dataset (KDD Cup 1999), the SVM-RF obtains highest accuracy of 99.42%, followed by SVM-LR-RF at 99.02%, SVM-LR at 98.03%, and LR-RF at 98.43%. Precision score of 99.94% was achieved by the LR-RF, and trailed by the SVM-RF at 99.91%, the SVM-LR at 98/90%, and LR-RF at 96/88%. With the recall measure, the SVM-LR-RF ensemble model attained the highest score of 99.01%, following is the SVM-RF model at 98.84%, SVM-LR at 96.85%, and LR-RF at 96.68%. The F1-score of 99.37% was obtained by SVM-RF model, the biggest margin, outperforming SVM-LR-RF at 98.95%, LR-RF at 98.28%, and 97.86%. The misclassification performance of the SVM-LR-RF model was best with type I error of 0.89% and type II error of 1.11%.

Table 9 shows the performances of the ensemble models using CSC-CIC-IDS2018 dataset for the various measures.

Table 9. Summary of the ensemble models' performances with CSE-CIC-IDS2018 dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC ROC (%)	Type I Error (%)	Type Error II (%)	Runtime (s)
Without ENN-SMOTE technique								
SVM + LR+ RF	94.11	96.04	96.49	96.26	90.91	13.17	3.96	31.98
SVM + RF	95.91	99.35	95.43	97.35	96.56	14.71	0.65	31.92
SVM + LR	90.57	95/96	91.88	93.88	88.82	8.48	4.04	23.90
LR + RF	93.53	99.32	92.40	95.74	95.04	22.27	0.68	5.64
With ENN-SMOTE technique								
SVM + LR+ RF	92.06	99.06	90.76	94.73	93.79	26.01	0.94	37.23
SVM + RF	91.41	99.68	89.36	94.24	94.15	28.37	0.32	34.26
SVM + LR	85.56	99.06	82.42	89.98	89.77	40.01	0.94	28.54
LR + RF	86.88	99.67	83.60	90.93	91.29	37.90	0.33	9.64

On the other hand, Table 9 presents the multi-class dataset (CSE-CIC-IDS2018) resampled with the ENN-SMOTE method gave the high accuracy score of 92.06%, immediate undertaken by SVM-RF at 91.41%, LR-RF at 86.88%, and lastly by SVM-LR model at 85.56%. In terms of precision measure, SVM-RF got 99.68% to place best, LR-RF (99.67%); while SVM-RF and LR-RF-SVM at 99.06% were the joint lowest. Considering the recall score, the SVM-LR-RF model had the biggest value of 90.76%, closely underperformed by SVM-RF at 89.36%, LR-RF at 83.60%, and SVM-LR at 82.42%. The highest F1-score of 94.73% was computed for the SVM-LR-RF model, and the rest following: SVM-RF (94.24%), LR-RF (90.93%), and SVM-LR (89.98%). In terms of misprediction scores showed that, the SVM-LR-RF model produces the least type I error of 26.01% and type II error of 0.94%, which implies the high classification rate.

The various dataset sizes (10-folds) and matching time complexity measured for the two datasets. The distinct ensemble models were trained and validated using 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% of the KDD Cup 1999 data as presented in Figures 2.

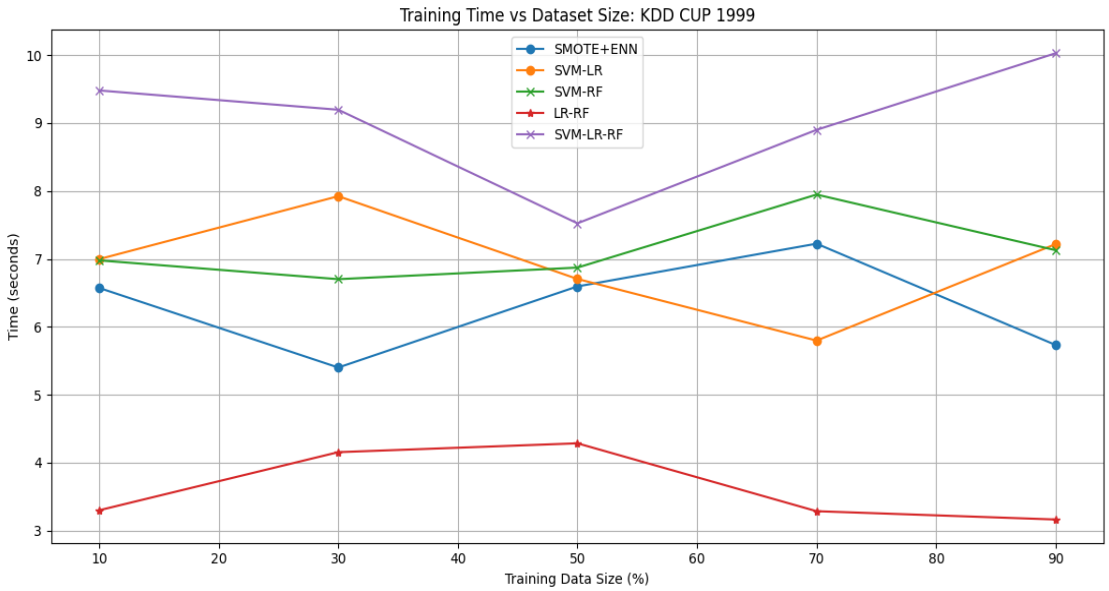


Figure 2: The ensemble models time complexity measured during training and validation phases with KDD CUP 1999 dataset.

In Figure 2, the SVM-LR-RF model commenced the training and validation phases at runtime of 9.5s at 10% of data, then decrease to lowest runtime of 7.5s at 50% of the data. Thereafter, the SVM-LR-RF model's runtime increases with additional data to peak at 10s upon full data usage. On the opposite, the LR-RF model took lowest runtime of 2s at 10% of data and increases until 50% data usage at runtime of 4.2s before sliding to 3.1s upon full data training and validation phases.

The several ensemble models were trained and validated with 10-fold sizes of the CSE-CIC-IDS2018 dataset are presented in Figures 3.

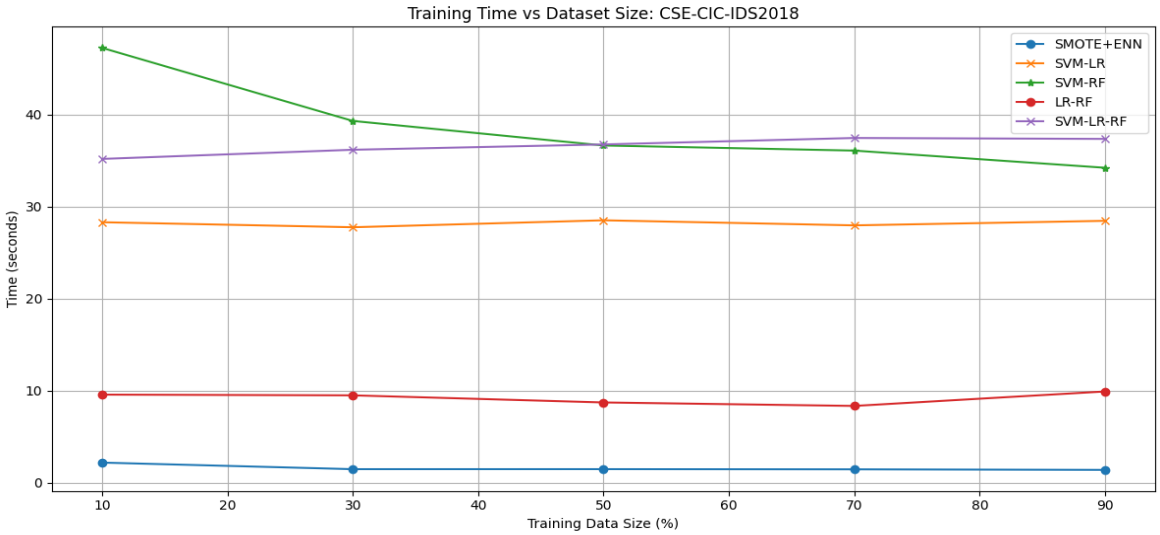


Figure 3: The ensemble models time complexity measured during training and validation phases with CSE-CIC-IDS2018 dataset.

From Figure 3, the SVM-LR-RF model started the training and validation phases at runtime of 35s at 10% of data, then increases steadily until 90% of data with runtime of 38s. Similar to the tends presented in Figure 2 for the LR-RF model, the runtime of 28s was observed at the 1st fold of data, and relatively steady after 9th fold of the data at 28.8s to terminate model's training and validation phases.

4.6 Discussion of findings

The paper introduced the ENN-SMOTE technique to address overfitting, noise reduction and class distribution balancing. This approach raises the hybrid ensemble models' performances in the cases of binary-class and multi-class data used for the validation phases. The SVM-LR-FR model offers more superior interpretability, less computational overhead, and better generalizability for multi-class datasets than binary-class data in case of intrusion detection tasks. It was found that, multi-class datasets require more corporation and synergy of the weak learners within the hybrid/ensemble models; thereby minimizing the potential redundancy as it is the case of the binary-class due to lower noise and fewer class distribution using ENN-SMOTE method.

The misclassification performance of the SVM-LR-RF model achieves the type I error of 0.89% and type II error of 1.11% for KDD Cup 1999 dataset, and the type I error of 26.01% and type II error of 0.94% for CSE-CIC-IDS2018 dataset. These imply that, the effectiveness of the ensemble models with larger size of weak classifiers for different resampled class of datasets.

The runtime complexity of training and validation of the SVM-LR-RF model was largest at 38s followed by the LR-RF model at the runtime of 28.8s using CSE-CIC-IDS2018 dataset. The opposite was the case of KDD CUP 1999 dataset in that, the LR-RF model had the fastest runtime of 3.1s, and the SVM-LR-RF model's runtime was biggest at 10s. These explain the influence of data size on the runtime performances of the ensemble models.

The Wilcoxon Signed Ranks Test measures the related samples from the RFE-based data preprocessing approach (bet) against ENN-SMOTE technique. The samples were drawn from the classification results, and type I error, and type II error computed. The Asymptotic Significance (2-sided test) p-value = 0.043, which less than the significance level of 0.05. This implies that, the median differences between the data samples of RFE and ENN-SMOTE techniques are NOT equal to 0. The null hypothesis is rejected. The paper established that, that the ensembles models with ENN-SMOTE performance increases caused significant differences.

5 Conclusion

The paper established four hybrid models by mixing SVM-RF, SVM-LR, LR-RF, and SVM-LR-RF models to raise the accuracy and minimize rate of false-alarms during the intrusion detection on enterprise networks. The two standard intrusion datasets belong to binary-class and multiclass, then preprocessed with ENN-SMOTE imbalance class and denoising solution. The resampled datasets were used for the training and testing of ensemble

models developed. The results indicated that, focusing on the binary-class dataset (KDD Cup 1999), the SVM-RF obtains highest accuracy of 99.42%, followed by SVM-LR-RF at 99.02%. Precision of 99.94% for LR-RF was highest, and the SVM-RF at 99.91% in second place. For the recall measure, the SVM-LR-RF model attained 99.01% and the SVM-RF model at 98.84%. The F1-score of 99.37% for the SVM-RF model, and SVM-LR-RF at 98.95% were highest.

On the contrary, the multi-class dataset (CSE-CIC-IDS2018) resampled with the ENN-SMOTE method offered accuracy of 92.06%, and SVM-RF at 91.41%. The precision score of 99.68% was highest for the SVM-RF, before the LR-RF at 99.67%. Focusing on the recall measure, the SVM-LR-RF model had the widest margin of 90.76%; thereafter the SVM-RF at 89.36% was closest. The F1-score of 94.73% for the SVM-LR-RF model was biggest before SVM-RF (94.24%).

The SVM-LR-RF model achieves the lowest misprediction for type I error of 0.89% and type II error of 1.11% for KDD Cup 1999 dataset. The same trend of misprediction for the type I error of 26.01% and type II error of 0.94% in CSE-CIC-IDS2018 dataset. The ensembles models' performances were largely satisfactory before of their relative high margin of values computed for the evaluation metrics. The reasons are due to the hard voting in which majority vote from the sets of decision trees from the single models when the final decision are made during classification tasks. Also, the ENN-SMOTE method is excellent for removing noise and balancing classes of datasets. Therefore, the SVM-RF and SVM-LR-RF ensemble models are the most effective classifier when dealing both the binary-class and multi-class data for the network intrusion detection.

These findings suggest that the proposed models not only enhanced the intrusion traffic detection rates but also adapts well with the complexities of real-world network traffic behaviours. By integrating the proposed ensemble models for advanced intrusion detection systems, organizations can significantly bolster their cybersecurity posture against increasingly sophisticated threats rather data feature redundancy removal. Future works could explore other high-performance classifiers, SMOTE techniques and more complex dataset to enhance detection capabilities and computational complexity of the proposed ensemble models. Again, it may interest to investigate the effect of combining the data preprocessing approaches of SMOTE and RFE techniques on performances of the hybrid models.

Code Availability

Authors shall provide the source codes utilized in the paper upon reasonable request-only.

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Hyperparameter Optimization for Malicious URL Detection: Leveraging Optuna and Random Search in Machine Learning and Deep Learning Models

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Keywords: Malicious URLs, hyperparameter optimization, Optuna, random search, BERT, LightGBM

Received: May 2, 2025

Uniform Resource Locators (URLs) are critical indicators for identifying malicious online activities such as malware distribution, phishing attacks, and website defacement. This research presents a robust approach for detecting these threats using both deep learning (DL) and machine learning (ML) techniques. We emphasize hyperparameter optimization, employing Optuna—a Bayesian optimization framework—and Random Search to systematically enhance model performance. Unlike many prior studies, which often overlook thorough hyperparameter tuning, our approach demonstrates improvements over state of the art methods. Our Bidirectional Encoder Representations from Transformers (BERT) model achieved an accuracy of 98.84%, with an F1 score of 99.02%, while the Light Gradient Boosting Machine (LightGBM) attained an accuracy of 98.46% and an F1 score of 98.45%

Povzetek: Prispevek predstavi optimizacijo hiperparametrov za zaznavanje zlonamernih URL-jev z uporabo Optuna in Random Search v modelih BERT in LightGBM, kar izboljša zaznavanje nevarnosti.

1 Introduction

The Internet has experienced rapid expansion in recent years, becoming an essential part of daily life in the digital age. It serves as a global communication platform and a vast repository of information across sectors such as government, business, academia, and personal use. With the widespread adoption of smartphones and increasing connectivity, users can now access online content from anywhere. However, this accessibility also exposes them to both reliable and malicious sources, increasing their vulnerability to cyberattacks and online fraud.

Malicious websites are frequently employed in cyberattacks to steal sensitive user data. Attackers often create counterfeit websites that closely resemble legitimate ones, deceiving users into unknowingly submitting personal information [1]. According to the Anti-Phishing Working Group (APWG), phishing attacks are escalating. In Q3 2024 alone, 932,923 phishing attempts were recorded—an increase from the previous quarter—with social media platforms being the most targeted sector, accounting for 30.5% of all attacks [2]. Additionally, reports indicate that over 40,000 new malicious URLs are created daily, resulting in estimated financial losses of $17,700 per minute [3].

One notable example is the February 2025 Bybit exchange hack, in which attackers exploited standard wallet transfer procedures to steal approximately $1.5 billion in Ethereum [4]. This incident highlights the evolving sophistication of cyber threats and the urgent need for robust detection mechanisms.

URLs serve as the unique identifiers of websites, determining their location and access methods. When users access a URL, it typically connects to a server's database and returns the website's content. URLs may be benign or malicious. In phishing attacks, malicious URLs closely imitate legitimate ones, often distributed via email or deceptive ads. Once clicked, these links may download malware or redirect users to credential-stealing sites. Given the large number of new websites created daily and the growing sophistication of cyberattacks, accurately distinguishing between benign and malicious URLs has become increasingly challenging.

Due to the structural similarities between benign and malicious URLs, effective classification requires extracting and analyzing specific features. The ease with which attackers can now create harmful URLs underscores the need for automated, scalable, and accurate detection methods. Recent research has turned to Machine Learning (ML) approaches to enhance malicious website detection. However, most existing solutions focus on individual web pages and rely on manually extracted features (such as text or images), limiting their scalability and generalization across diverse domains [5, 6].

In this paper, we propose an advanced approach for malicious URL detection by integrating deep learning and traditional ML with automated hyperparameter optimization. Specifically, we develop two models: (1) a BERT-based classifier enhanced with Optuna for automated hyperparameter tuning, leveraging BERT's powerful contextual understanding to capture subtle patterns in URL structures, and (2) a lightweight yet effective LightGBM classifier optimized with Random Search to balance performance and

computational efficiency.

The primary contributions of this work are as follows:

- We introduce a BERT-Optuna model that combines contextual language modeling with automated hyperparameter tuning to improve malicious URL detection accuracy.
- We develop a LightGBM-Random Search model to efficiently explore hyperparameter space for robust and interpretable detection results.
- We conduct a comprehensive evaluation of the proposed models on a real-world dataset of over 650,000 URLs.
- We perform a comparative analysis against state-of-the-art classifiers to validate the effectiveness of our approach.

The remainder of this paper is structured as follows: Section 2 reviews related work. Section 3 presents our preprocessing techniques. Section 4 outlines the classification methods. Section 5 describes the proposed models. Section 6 details the experimental setup and evaluation metrics, and Section 7 presents and discusses the results. Finally, Section 8 concludes the paper and outlines directions for future research.

2 Related research

In this section we are going to explain the methods used to detect malicious URLs. Prior studies have explored harmful URL detection and classification via diverse ML and DL methods, yielding varying accuracy percentages. These studies have enhanced the comprehension of efficient methodologies and techniques for detecting and categorizing malicious URLs. In order to evaluate the contribution of these methodologies in comparison to earlier research, we have collected different contents of articles and sources to uncover characteristics or trends that separate benign from malicious url. These methodes use various algorithms to classify and detect malicious URLs.

Su and Su[7] suggested BERT-based harmful URL detection. By tokenizing URL strings with BERT, the self-attention mechanism may understand their semantic linkages. The model uses raw URL strings or Random Forest feature strings, depending on the dataset. BERT is fine-tuned against public datasets (Kaggle, GitHub, ISCX 2016) and adaptable to multiple data formats, delivering excellent classification accuracy 98.78%, 96.71%, and 99.98% on the three datasets.

Nanda, Saraswat, and Sharma[8] proposed a phishing URL detection model using Bidirectional Long Short-Term Memory (BiLSTM), Convolutional Neural Networks (CNN), and a Gated Highway Attention (GHA). The model has several key steps: pre-processing URLs to a uniform length of 255 characters; BiLSTM and CNN work together to extract both global and local features; highway networks improve information flow to deal with problems like vanishing gradients; attention mechanisms are used to improve feature learning and reduce the effect of irrelevant data; the model achieved better performance metrics, with an accuracy of 99.78%, precision of 98.97%, recall of 99.35%; beating other traditional ML and DL techniques.

Wang et al.[9] provided a DCNN malicious URL detection model. A dynamic convolution technique replaces the pooling layer with a k-max pooling layer and adds a folding layer. The pooling settings are dynamically modified based on the input URL length and convolutional depth to extract deeper features. The model uses character-level and word-level embedding to represent unusual words and special characters while minimizing memory usage. This hybrid embedding achieved an accuracy of 98.7% and 98.7% as F1-score.

The work of Sheikhi and Kostakos[6] configures a hybrid approach combining the Firefly Algorithm for feature selection and Particle Swarm Optimization (PSO) for optimizing XGBoost hyperparameter improving malicious website detection. The hybrid model achieved an astonishing 98.42% accuracy and an F1-score of 98.4% in binary classification, while it yielded a multiclass classification accuracy of over 98%.

The research of Gupta et al.[10] shows how ML-based URL lexical characteristics can detect phishing. The technique constructs nine lexical features—token count, URL length, and domain delimiters—and uses Random Forest, K-Nearest Neighbors (KNN), Logistic Regression, and Support Vector Machine (SVM) classifiers. The approach requires no third-party information, enabling real-time performance with low computational resources. Random Forest had the highest accuracy of 99.57%, a low false positive rate of 0.53%, and a rapid run time of 51.5ms.

Ullah et al.[11] proposed a multi-model visual representation and transformers-based transfer learning explainable malware detection system is presented. The malware categorization method uses network traffic text and images. BERT extracts first-learned textual properties from HTTP and TCP flows. After feature extraction using the FAST extractor and BRIEF descriptor, a malware-to-picture transformation transforms network byte streams into images. After class imbalance is resolved via Synthetic Minority Over-Sampling (SMote), CNN deep feature extraction is performed. A voting-based ensemble learning approach leads the final categorization. Malware detection and classification rates of 98.44% and 99.16%.

Wu et al.[12] proposed an NLP method based on a bidirectional gated recurrent unit (BiGRU).It used The dropout mechanism in the input layer to avoid overfitting, the attention mechanism in the middle layer to learn the correlation between sequences, Word2Vec for the preprocessing to train the word vector of URLs and the BiGRU to extract all the sequence information of URLs. This proposed method (DA-BiGRU) achieved better experimental results in detecting malicious URLs than the MLP, Att-BiLSTM,

Att-BiGRU, DA-BiLSTM with an accuracy of 0.9792, precision of 0.9834, reacall of 0.9553 and F1 score of 0.9691.

Alshingiti et al.[13] proposed a DL technique to detect phishing URLs. This methodology employs Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and a hybrid LSTM−CNN model. The three systems adhere to a four-step process: extracting features, preprocessing data using SelectKBest for feature selection and MinMaxScaler for scaling, training the models, and ultimately categorizing URLs as legitimate or phishing. They refined hyperparameters such as number of layers, dropout rate, learning rate, number of epochs and batch size to improve performance. Among the models, CNN achieved the highest accuracy at 99.2%, surpassing LSTM−CNN at 97.6% and LSTM at 96.8%.

R, Patil, and Mohana[14] proposed a malicious URL detection and classification method using machine learning. The method utilizes a dataset of 651,191 URLs, categorized into Phishing, Benign, Defacement and Malware types. Three machine learning algorithms, Random Forest, LightGBM and XGBoost, were implemented. The models were trained and validated on the dataset, and their performance was evaluated using metrics like accuracy, precision, recall and F1 score. The Random Forest classifier achieved the best results with an accuracy of 96.6%.

Alsaedi et al.[15] introduced the CTI-MURLD model for the detection of malicious URLs, which incorporates various data sources such as URL content features, Google-based Cyber Threat Intelligence (CTI), and Whois-based CTI. Utilizing external threat intelligence. The model comprises several phases: Data preprocessing involves the application of NLP techniques to normalize textual data. Feature extraction through N-gram and TF-IDF. Feature Selection: Mutual Information is employed to select the 5000 most informative features. Ensemble Learning for Classification employs a two-stage ensemble approach: Three Random Forest classifiers are trained independently on separate feature subsets: URL features, Google-CTI, and Whois-CTI. The probabilistic outputs from the RF classifiers are aggregated and input into a Multi-Layer Perceptron (MLP) neural network, which is optimized using the BFGS quasi-Newton algorithm to enhance weight tuning and accelerate convergence. Grid Search was employed to optimize performance, as Random Forest algorithms necessitate meticulous hyperparameter selection, increased accuracy and reduced false positive and false negative rates relative to baseline models. The best result was that of RF + GS with an accurcy of 97.25%,recall of 97,26% and a precision of 97.36%.

Yu et al.[16] The study proposed an improved M-BERT model for malicious URL detection, leveraging Transformer encoders for feature extraction and classification. It outperformed traditional methods, achieving 94.42% precision. Future work focuses on scalability, multimodal data integration, and privacy protection using federated learning.

Maneriker et al.[17] introduce URLTran, a phishing URL detecting transformer-based model. URLTran achieves a true positive rate (TPR) of 86.80% at a 0.01% false positive rate (FPR), a 21.9% improvement over past DL models such as URLNet by adjusting BERT and RoBERTa and including domain-specific pre-training. After adversarial fine-tuning, the model is tested against adversarial attacks like homoglyph replacements and compound word splitting, hence proving increased resilience.

Mankar et al.[18]conducted a comparative evaluation of machine learning models for malicious URL detection. The study utilized a dataset of over 500,000 URLs and examined models including decision trees, random forests, KNN, and Naive Bayes. Feature engineering was employed to transform URLs into numeric features for model training. The Random Forest and Extra Trees ensemble models achieved the best performance, demonstrating over 91% accuracy in distinguishing between benign and malicious URLs. The findings indicate the potential of ensemble machine learning techniques for automated malicious URL detection.

The following table 1 summarizes those findings of several research studies.

3 Methodology

The proposed methods are designed to develop innovative models for accurately detecting malicious websites. The implementation details, dataset, and summary of the proposed models are all detailed in this section.

3.1 Data collection

In this research, we evaluated the proposed models using a malicious URL dataset sourced from [19]. The dataset consists of a total of 651,191 URLs, categorized into four distinct classes: benign, defacement, phishing, and malware. The primary goal is to use this dataset to develop ML and DL models capable of identifying malicious URLs to prevent some of cybersecurity threats.

Distribution of URLs

Here is the distribution of URLs in the dataset as shown in the table 2:

The dataset is curated from five different sources to ensure a comprehensive collection of URL examples. The sources include ISCX-URL-2016, Malware Domain Blacklist, Faizan Git Repository, Phishtank, and PhishStorm datasets [20]. The dataset is structured in a tabular format with two main columns: URL and Label. The URL column contains the actual web addresses, and the Type column indicates the category of each URL (benign, defacement, phishing, or malware) as in Figure 1.

Table 1: Literature review

Work	Dataset	Methodology	Feature Engineering	Hyperparams optimization	Results (%)	Limitations
[7], 2023	Kaggle, GitHub, ISCX-URL-2016	BERT+self-attention mechanisms+Classifier	RF + SMOTE	–	Acc1: 98.78, Acc2: 96.71 , Acc3: 99.98 respectively	Limited zero-day attack handling
[9], 2021	GitHub, Kaggle, Alexa	DCNN	Word Embedding Based on Character Embedding	–	Acc: 98.7, F1: 98.7, P: 99.3, R: 98.1	High computational cost
[6], 2024	ISCX-URL-2016	XGBoost	Firefly Algorithm + CFSSubsetEval	Partical Swarm Optimization(PSO)	Binary Acc: 98.42, Multi Acc: 98	Needs real-world validation
[10], 2021	ISCX-URL-2016	ML (RF, KNN, SVM, LR)	Lexical Features + Feature Selection	–	Acc: 99.57, P: 99.7, R: 99.46, F1: 99.58	Ignores content-based features
[11], 2022	CICMalDroid 2020+CIC - InvesAndMal2019	BERT	FAST extractor,BRIEF descriptor	–	Acc: 99.16, F1: 98.44	Possible flaws include the method's computational complexity
[12], 2022	Kaggle	BiGRU	Word2Vec + Dropout + Attention	–	Acc: 97.92, P: 98.34, R: 95.53, F1: 96.91	Needs optimization
[8], 2024	Web Phishing Dataset	BiLSTM + HABCNN	Word2Vec + Feature Extraction	–	Acc: 99.78, P: 98.97, R: 99.35, F1: 98.99	Struggles with shortened URLs
[13], 2023	ISCX-URL2016	CNN, LSTM, CNN-LSTM	SelectKBest + MinMaxScaler	–	Acc: 99.2, P: 99, R: 99.2, F1: 99.2	Ignores URL activity status
[17], 2021	Microsoft Edge+Internet Explorer telemetry	BERT, RoBERTa	WordPiece Tokenization	–	Acc: 99.67, F1: 99.71	Advanced reinforcement learning-based attacks could weaken the model
[14], 2023	651,191 URLs (Kaggle)	ML (Random Forest, LightGBM, XGBoost)	Feature extraction (counts, lengths, lexical tokens), PCA	Manual tuning	ACC: RF: 96.6%, LGBM: 95.6%, XGBoost: 93.2%	basic hyperparameter optimization
[15], 2022	Various sources (URL, Google CTI, Whois CTI)	CTI-MURLD: Two-stage ensemble (RF + MLP) with BFGS optimization	URL content features, Google-based CTI, Whois-based CTI, N-gram, TF-IDF, Mutual Information for feature selection	Grid Search	RF + GS: 97.25% accuracy, 97.26% recall, 97.36% precision	Complex architecture, requires extensive feature engineering
[16], 2024	Dataset of URLs	Improved M-BERT model using Transformer encoders	Implicit feature extraction via DL (Transformer-based)	–	Precision: 94.42%	Scalability and multimodal data integration not yet addressed, future work needed

3.2 Bidirectional encoder representations from transformers (BERT)

It is a pre-trained language model trained on 3.3 billion English tokens using two objectives: masked language modeling and next sentence prediction. It uses special tokens like [CLS] and [SEP] to structure inputs and enable context-aware understanding. The base version of BERT consists of 12 transformer layers with 12 attention heads each, and can be fine-tuned to achieve high performance across various

Table 2: Distribution of URLs in the dataset

Type	Total	Percentage
Benign URLs	428,103	65.72%
Defacement URLs	96,457	14.81%
Phishing URLs	94,111	14.45%
Malware URLs	32,520	5.00%

	url	label
0	br-icloud.com.br	phishing
1	mp3raid.com/music/krizz_kaliko.html	benign
2	bopsecrets.org/rexroth/cr/1.htm	benign
3	http://www.garage-pirenne.be/index.php?option=...	defacement
4	http://adventure-nicaragua.net/index.php?optio...	defacement

Figure 1: URL dataset

NLP tasks such as sentiment analysis and question answering [21].

3.3 Light gradient boosting machine (LightGBM)

It is a decision tree-based boosting algorithm designed to be fast and efficient on large datasets. It uses two main techniques: GOSS (Gradient-based One-Side Sampling) to reduce computational costs, and EFB (Exclusive Feature Bundling) to reduce dimensionality. These approaches allow LightGBM to be faster than conventional methods while maintaining high accuracy [22].

This two algorithms have been used in the proposed classification model to identify malicious websites with the highest accuracy.

3.4 Data preprocessing

Preprocessing is a critical step in any classification task, especially in the context of unbalanced text data such as malicious URLs. Our preprocessing pipeline was carefully designed to meet the specific requirements of each of the two models (BERT and LightGBM), while ensuring overall consistency in data preparation.

Cleaning: URLs were first converted to lowercase to standardize case. Duplicates were then removed, resulting in a 1.56% reduction in the total data volume.

Target Encoding: The label corresponding to the URL type (benign, phishing, malware, defacement) was processed using LabelEncoder strategy to transform classes into integers

URL Tokenization: The vector representation of URLs was adapted to the two methods we used:

- **For BERT model**: Tokenization was performed using the tokenizer `bert-base-uncased`, with a maximum sequence length set to 256 tokens. This step includes truncation, masking of special tokens `[CLS]`, `[SEP]`, and padding.

- **For LightGBM model**: TF-IDF vectorization [23] (Term Frequency Inverse Document Frequency: which is a traditional text analysis method that determines the importance of a word by calculating its frequency in the document and its inverse document frequency across the document set [24]) was applied, using **character n-grams** of size 1 to 3 filters out overly frequent terms (max_df = 0.85) and rare terms (min_df = 10). The maximum number of features (`max_features`) was set to 120,000, allowing the extraction of relevant syntactic patterns while maintaining a manageable vector space.

3.4.1 Dataset partitioning

A stratified partitioning of the dataset was performed to preserve class distributions across all subsets as shown in figure 2. The data was initially divided into two main sets: 85% for model development and 15% as a held-out test set used exclusively for final evaluation. To reduce computational cost during hyperparameter optimization (HPO), a stratified 20% subset of the 85% development set was sampled. HPO was performed on this subset. Once optimal hyperparameters were identified, the final models were retrained on the full 85% development set and evaluated only on the untouched 15% test set, ensuring that performance metrics reflect true generalization ability.

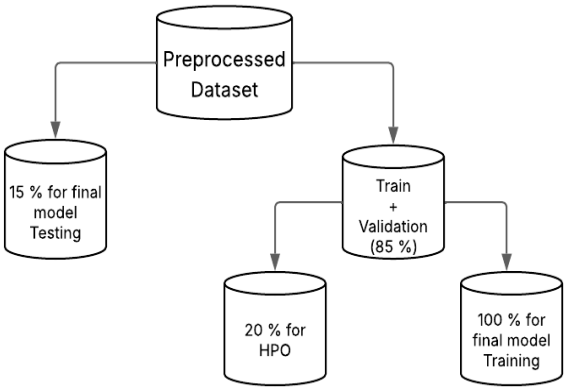


Figure 2: Dataset spliting

3.5 Optuna

A modern optimization framework that efficiently searches for optimal hyperparameters using pruning and dynamic trial allocation, its architecture is shown in Figure 3

Optuna is an emerging tool with three advantages for model selection or hyperparameters determination. The first advantage Optuna provides is the define-by-run style API. The second advantage is an efficient pruning and sampling mechanism. The third advantage is that it is easy to set up.[25]

This approach uses the Tree-structured Parzen Estimator (TPE) algorithm, which is an efficient Bayesian approach to optimize continuous and discrete search spaces. This algorithm constructs a probability distribution of hyperparameters by distinguishing promising configurations from poor performers[26].

3.6 Random search

The random search method involves testing a set number of random combinations of hyperparameters, followed by evaluating their performance and selecting the best results. This approach is efficient and works well with high-dimensional data. The process consists of several steps: first, the number of iterations (n_iters) is set; then, all parameter values are initialized to zero. In each iteration, the parameter values are randomly adjusted, and the model is trained on the data. The classifications are tested using real data to evaluate the performance, and the best parameter values and classification results are saved for future use [28].

4 Classification methods

Our work shows how hyperparameter optimization affects DL (BERT) and ML (LightGBM) models, which are frequently used but rarely fine-tuned. Our approach to optimization is rigorous: for BERT, we use Optuna to tune key hyperparameters like learning rate, batch size, number of epochs and dropout; for LightGBM, we use random search to adjust tree depth, learning rate, number of leaves and others. To reduce computational cost, we performed hyperparameter optimization (HPO) on a stratified 20% subset drawn from the 85% training/validation portion of the data. This ensures both efficiency and class representativity. The optimal hyperparameters were then applied to retrain models on the full 85% development set. Final evaluation was conducted on the held-out 15% test set, never seen during training or optimization.

5 Hyperparameter optimization

Hyperparameter optimization is a crucial step in the training process for ML and DL models. Careful hyperparameter configuration can significantly improve a model's performance, particularly in unbalanced classification contexts such as malicious URLs. In this study, we explored two distinct optimization strategies tailored to the nature of the models used.

5.1 BERT-Optuna model

Our first model is based on the BERT architecture and is specifically designed for malicious URL classification. We use the bert-base-uncased variant, which contains 110 million parameters and has proven effective for sequence classification tasks. To enhance performance, we applied a Bayesian hyperparameter optimization approach using Optuna's Tree-structured Parzen Estimator (TPE) algorithm, which efficiently explores the search space. The objective of the optimization was to maximize the weighted F1-score, a suitable metric given the class imbalance in our dataset. The model architecture is illustrated in Figure 4.

The hyperparameter search space included the following: learning rate, batch size, dropout rate, and number of epochs. Their respective ranges and results are presented in Table 3. In response to the structural characteristics of URLs and the imbalance in class distribution, we also introduced several adaptations. Notably, we used automatically computed class weights, inversely proportional to class frequencies, within the CrossEntropyLoss function to improve minority class recognition. Additionally, we limited input sequences to 256 tokens, striking a balance between information preservation and computational efficiency.

5.2 LightGBM-RandomSearch model

Our second approach presents a comparative study of two LightGBM-based architectures for malicious URL classification, highlighting the importance of preprocessing and hyperparameter optimization. Initially, we evaluated a baseline LightGBM model using default parameters, coupled with carefully tuned TF-IDF vectorization settings. To enhance performance and mitigate overfitting, we then applied systematic hyperparameter tuning via RandomizedSearchCV, enabling efficient exploration of a large search space with lower computational overhead compared to exhaustive methods. The model architecture is illustrated in Figure5.

The optimization process focused on key parameters: number of leaves and maximum tree depth to manage model complexity, learning rate and number of estimators to influence training dynamics, feature_fraction and bagging_fraction for subsampling and robustness. We also tuned the number of boosting iterations to control overall complexity. The full range of explored hyperparameters and their optimal values is detailed in Table 4. Overall, the final model achieved a strong balance between expressiveness and generalization.

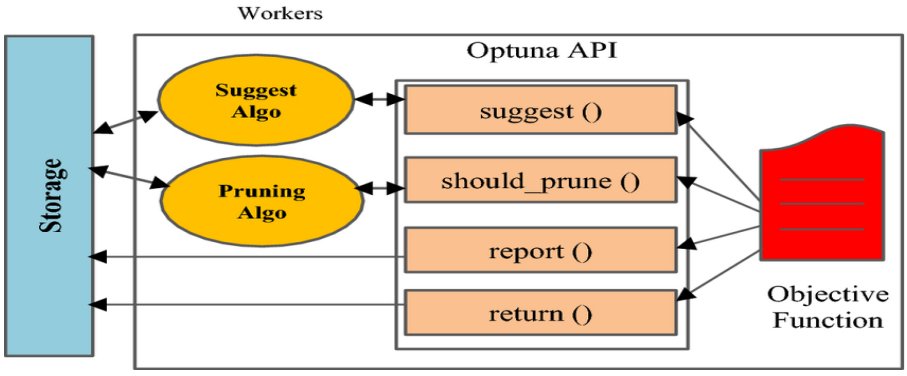


Figure 3: Overview of Optuna's system design [27]

Table 3: Hyperparameters optimization for BERT model

Hyperparameter	Value range	Optimal value
Learning rate	log-uniform between 1×10^{-5} and 5×10^{-5}	$3.49312729495079 \times 10^{-5}$
Batch size	{16, 32}	32
Dropout	[0.1, 0.5]	0.1479659107702988
Number of epochs	4 to 10 with early stopping	6

6 Experimental setup

In this section, we look at the experimental setup.In subsection 6.1, the performance evaluation metrics that will be used to judge how well the suggested method works are explained. Subsection 6.2 explains how the experiment was set up and how it was done.

6.1 Evaluation metrics

In the experiments, to improve the evaluation effectiveness of the proposed models, we utilized several recognized metrics, namely the F-measure, precision, recall, classification accuracy (ACC) and ROC-AUC (Area under the Receiver Operator Characteristic Curve). In confusion matrix, TP represents entries that are appropriately categorized as malicious sites. FN is the number of entries mistakenly classified as harmful websites.The FP represents the mistakenly identified harmful sites. TN is the number of successfully detected authentic websites.

The classification accuracy **(ACC)** measures the proximity among assessments of projected records and the overall count of valid and harmful websites. The value of ACC is measured by Eq.1

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision: It is the proportion of webpages the suggested model successfully identified as harmful. It shows the proposed model's correctness. The value of precision is measured using Eq.2

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall: It indicates the proportion of harmful websites that were accurately identified as harmful. It shows the wholeness. It calculated using Eq.3

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F-measure: It is defined as the harmonic mean of precision and recall.It calculated using Eq.4

$$F - measure = \frac{2 \times Precision \times Recall}{Preciosion + Recall} \tag{4}$$

FAR: FAR is for False Acceptance Rate. It calculated using Eq.5

$$FAR = \frac{FP}{FP + TN} \tag{5}$$

AUC-ROC (Area under the Receiver Operator Characteristic Curve): lets you check how well the predicted classes match up with the real classes. If the AUC-PR score is high, it means that the model can tell the difference between negative and positive case points better. Most of the time, AUC values are shown on a range from 0 to 1, where:

- AUC = 0.5 shows that the model performs similarly to random guessing.
- AUC = 1 indicates that the classifier differentiates between negative and positive instances.

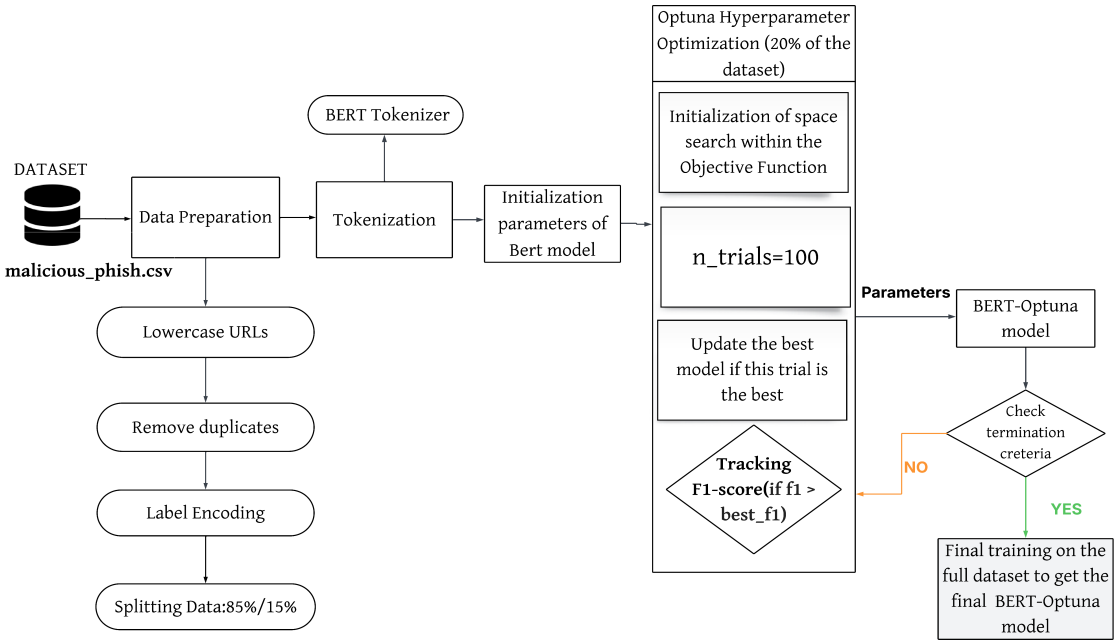


Figure 4: The proposed BERT approach

Table 4: Hyperparameters optimization for LightGBM model

Hyperparameter	Value range	Optimal value
num_leaves	[30, 80]	68
max_depth	[5, 15]	10
learning rate	[0.1, 0.25]	0.10560222831238217
n_estimators	[1800, 3000]	2443
feature fraction	[0.5, 0.9]	0.6091500749817148
bagging fraction	[0.5, 1]	0.959083326056901
max_bin	[63, 255]	205
min_data_in_leaf	[5, 30]	23
num_iterations	[10, 1000]	912

6.2 System setup

The optimization and training of the BERT model were carried out on a server equipped with dual NVIDIA RTX 3060 GPUs, each offering 12 GB of dedicated memory, utilizing PyTorch 1.12 and Transformers 4.24 to fully exploit CUDA acceleration. The LightGBM model was trained and optimized in a Google Colab environment with access to 334 GB of RAM. Although the runtime type supported TPU acceleration, LightGBM computations were executed on the CPU, as the library does not support TPU-based processing. A range of Python libraries, including Scikit-learn, NumPy, SciPy, Pandas, and Matplotlib, were employed to develop and evaluate the proposed models.

7 Experimental results and discussion

The experimental results and performance metrics of Bert with Optuna optimization model, LightGBM with tunned TF-IDF model and LightGBM with Random Search optimization and tunned TF-IDF are shown in Table 5 and Figure 6.

All the results reported in this section were obtained on the 15% hold-out test set, which was never used during hyperparameter optimization or training. This ensures that the metrics accurately reflect the model's generalization performance.

7.1 Performance analysis

Bert-Optuna achieved the highest results with 99.02% F1-score, 98.84% accuracy, an AUC-ROC of 0.9982 and

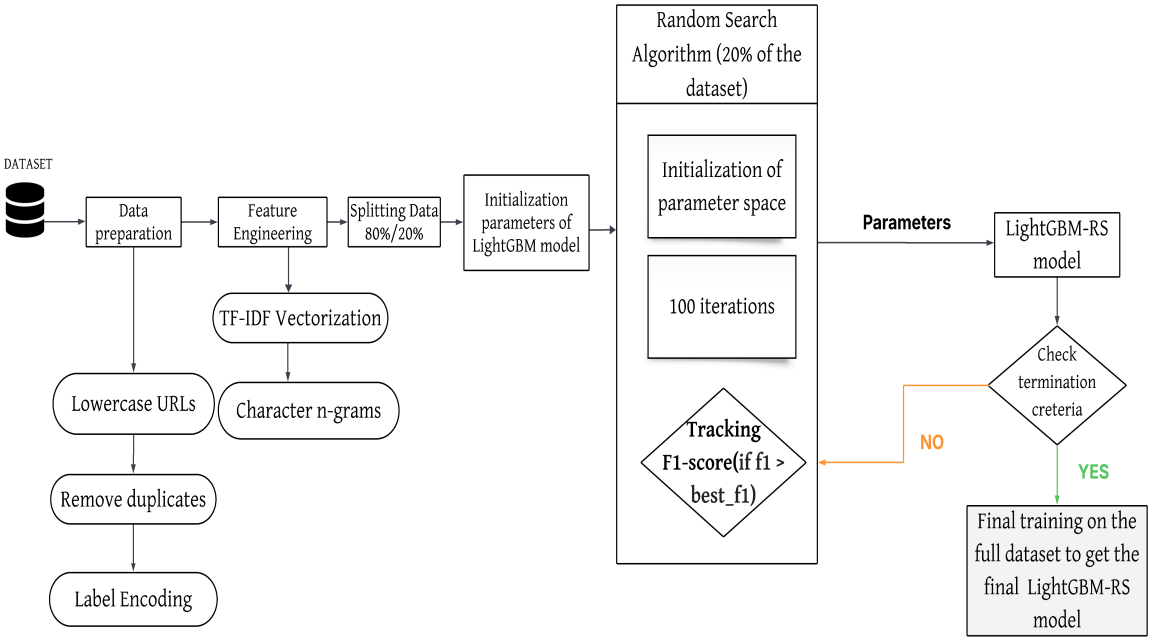


Figure 5: The proposed LightGBM framework

False Rate Alarm of 0.005, outperforming all other models. LightGBM-Tfidf-RandomSeach followed with 98.46% accuracy, 98.45% F1-score, and an AUC-ROC of 0.998, showing clear gains from Random Search optimization. Tfidf-LightGBM also performed well, reaching 97.63% accuracy and 97.61% F1-score using only TF-IDF tuning. These results highlight the impact of optimization and preprocessing on model performance.

7.2 Performance comparison with existing studies

Compared to the first part of Su and Su[7] on the Kaggle dataset, , our Optuna-BERT model improves the F1-score from 98.57% to 99.02% so reduces the false alarm rate. Similarly, in comparison to the work by R, Patil, and Mohana [14], our Tfidf-LightGBM and Tfidf-RandomSearch-LightGBM models show clear improvements, with accuracy rising from 95.6% to 98.46% and a higher AUC-ROC score. These comparisons confirm that our optimized models offer significant advancements over existing approaches in malicious URL detection.

7.3 Why did BERT outperform LightGBM and state-of-the-art models?

BERT's performance superiority stems from its deep contextual understanding of URL text sequences. Unlike LightGBM, which relies on static vectorized features (TF-IDF), BERT captures both token-level and sentence-level semantics. This makes it particularly effective in recognizing subtle variations that are common in malicious URLs.

Further, using a longer token length (256 vs. 128 in earlier studies) allowed BERT to retain more contextual information from long or obfuscated URLs. The optimized configuration — a lower dropout (0.15) and larger batch size (32) — helped enhance generalization and stability.

7.4 Role of hyperparameter optimization

Hyperparameter tuning played a pivotal role. For BERT, Optuna selected a learning rate of 3.462×10^{-5} and a dropout of 0.147, with early stopping after 6 epochs to prevent overfitting. These adjustments boosted model stability and performance, particularly on minority classes.

For LightGBM, random search optimization increased its capacity by selecting a larger number of leaves (68) and a tree depth of 10. At the same time, reducing the feature fraction to 0.61 improved generalization by encouraging diversity across trees. These improvements closed a significant part of the performance gap with BERT.

7.5 Handling class imbalance: per-class performance

The dataset exhibits class imbalance, with benign URLs overrepresented and phishing/malware underrepresented. This imbalance affected model sensitivity to minority classes. Table 6 provides a breakdown of per-class F1-scores:

BERT-Optuna achieved consistently high F1-scores across all classes, outperforming other models especially on the more challenging classes like phishing (97.11%) and mal-

Table 5: Performance comparison of malicious URL detection approaches

Research	Dataset	Model	Accuracy	Precision	Recall	F1 score
Su and Su [7]	Malicious urls dataset [19]	Fine-tuning BERT + Classifier	98.78%	99.12%	98.02%	98.57%
R, Patil, and Mohana [14]	Malicious urls dataset [19]	Light GBM Classifier	95.6%	95%	96%	95%
This study	Malicious urls dataset [19]	TF-IDF LightGBM	97.63%	97.61%	97.63%	97.61%
	Malicious urls dataset [19]	TF-IDF Random-Search Light-GBM	98.46%	98.45%	98.46%	98.45%
	Malicious urls dataset [19]	OptunaBERT	98.84%	99.20%	98.84 %	99.02%

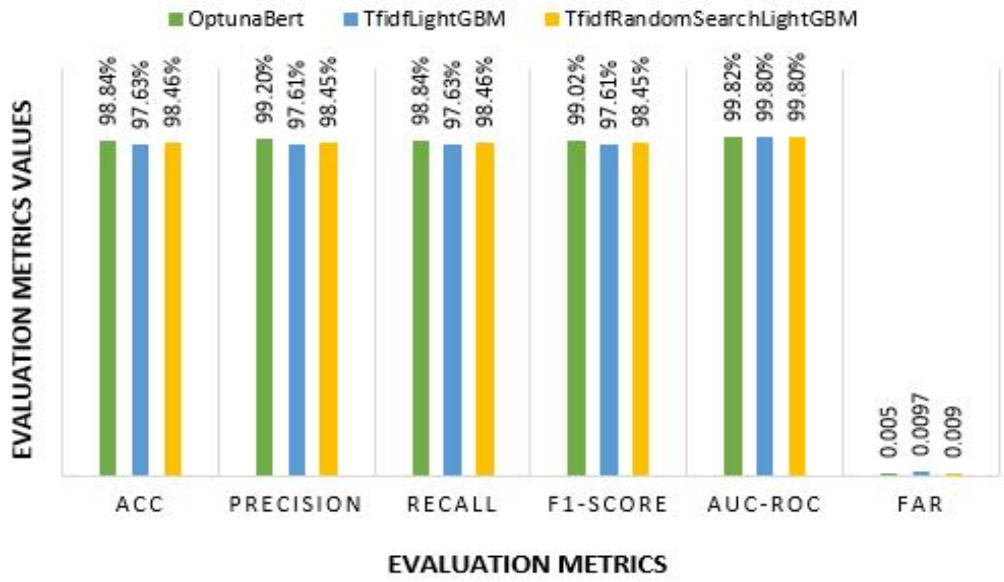


Figure 6: Comparison of the proposed models' evaluation metrics

ware (96.14%). This reflects the advantage of transformer-based architectures in capturing contextual features. In contrast, LightGBM-based approaches showed slightly lower F1 performance on phishing and malware, indicating some limitations in handling complex or possibly less-represented patterns.

8 Conclusion and future work

Malicious websites pose significant cybersecurity threats by targeting users to steal sensitive data and disrupt online activity. This study proposed a novel approach combining machine learning (ML) and deep learning (DL) techniques to effectively detect and classify such threats. We developed and evaluated two optimized models: (1) a BERT-based classifier enhanced with the Optuna hyperparameter optimization framework, and (2) a LightGBM model fine-tuned via RandomizedSearchCV to efficiently explore a wide hyperparameter space.

Experiments conducted on a real-world dataset containing over 651,000 URLs demonstrated the effectiveness of our approach. The Optuna-BERT model achieved an F1-

Table 6: Per-class performance (F1-score) comparison

Model	Benign	Defacement	Phishing	Malware
BERT-Optuna	99.32%	99.76%	97.11%	96.14%
LightGBM-TFIDF-RandomSearch	99%	99.98%	97%	95%
TFIDF-LightGBM	99%	99%	96%	92%

score of 99.02%, while the optimized LightGBM model reached 98.45% accuracy. These results outperformed several existing benchmark methods in terms of F1-score, false alarm rate, and AUC-ROC.

The study highlights the importance of combining advanced feature representations, contextual language modeling, and systematic hyperparameter optimization to enhance detection performance. It also shows that properly optimized classical models like LightGBM can still provide competitive results.

Future work will focus on extending the framework to detect evolving cyber threats in more diverse environments, such as IoT ecosystems. We also plan to investigate ensemble techniques and alternative feature extraction strategies to further improve robustness, scalability, and generalization across threat types and domains.

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Early Detection of Brain Tumors Using SOLOv3 Algorithm for Enhanced Diagnostic Accuracy

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Keywords: brain tumor, SOLOv3, machine learning, classification

Received: December 18, 2024

The brain tumor is various types occur in the human brain sometime it affects the human quality of life. The deep learning algorithms gives the better detection of the tumor cell with highly positive result in the earlier stage. In the previous work, the customized Segmenting Objects by Locations Vector 3(SOLOv3) algorithm has been approached, this approach gives the better result compared with the previous algorithms. In the medical field the radiographic images are plays the vital role for identifying the disease from the human body at the same time helps to give the proper treatment on time for avoiding the death ratio. There are many automatic image reorganization techniques were developed in deep learning algorithms. Since the proposed idea is to classify the images based on the plasma level and also detect the levels of infection specified as stage1 to stage 5. To use the Magnetic Resonance Images (MRI) for identifying the tissues which present the human organ with the neoplasm type and size. This kind of information's are helpful to treat the patient on time and also reduce the death rate due this late treatment or detection of the which level the person may affected. The aim of the proposed article is to develop the customized SOLOv3 algorithm with DESNET201 for improved image segmentation and classification. The real time images were taken from the prescribed reputed Neurological diagnosis center in Chennai. Totally 18759 images were collected under all four categories of tumor and non tumor. Which included 13257 images are tumor images under the category of glioma, meningioma and pituitary and remains comes under non tumor category. The implemented model is to customize the final layer of the neural network form with four different classes will give the better result as 91% in the training set and scored 89% as in the phase of test. This improved model that could combine the SOLOv3 and Desnet201 with customized layer classes for extracting the features used to classify the tumor cells with their different types. The tumor may have more than 150 types of tissues, but gradually these four kinds of classes are very dangerous about to increase the death and spreadable to other body organ. These techniques also able to detect the improved automation for the tumor in Indian children and adults.

Povzetek: Prispevek združuje algoritma SOLOv3 in DenseNet201 za zgodnje odkrivanje možganskih tumorjev iz MRI posnetkov ter poroča o izboljšani segmentaciji in klasifikaciji v pet razredov tumorjev.

1 Introduction

In recent years, sedentary behavior has emerged as the brain is the vital organ that governs the functioning of the entire human body. The brain provides instructions to other organs to do their respective functions without any interruption. The nervous system typically regulates the functions of the human body by transmitting signals to various components of the human organism. When the brain is in a healthy state, all human activities will be normal. Conversely, if the brain is in an unhealthy condition, all activities will be abnormal. The brain can become compromised by a range of factors, including tumors, genetic abnormalities, injuries, or familial problems. This article presents a novel approach for identifying cancerous cells in the brain. If the tumor cell is found early, it may be possible to remove it, even though there may not be a treatment for many causes. The explanation provided was thorough and focused on both the desired result and the practical application, with particular emphasis on the loss function. A brain tumor is an abnormal proliferation of tissues that originate and spread inside the human body, affecting other organs [1]. Tumors of different

sorts arise in the human brain and are categorized according to the dimensions and morphology of the cells in the affected region [2]. The provided (Figure 1) displays normal brain imaging on the left side and brain tumor pictures on the right side. Figure 1 displays two distinct brain types, one with an unhealthy tumor image on the left and a healthy brain image on the right. These images were obtained from MRI scans.

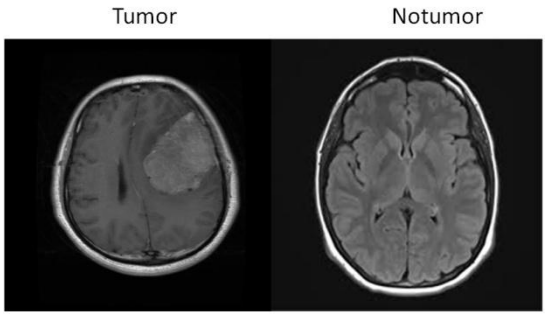


Figure 1: MRI scan comparison of a brain with a tumor (left) and a healthy brain (right).

According to the World Health Organization, there are around 150 different varieties of brain tumors. Not all types of tumors are dangerous to human life, since some are classified as low-grade. Certain cancers are classified as high-grade and pose a significant threat to human life. There are fewer than four types. It exhibits rapid proliferation and metastasis to both cerebral tissues and other bodily organs. It impairs cognitive function and leads to a decline in mental capacity. Living the regular life of a human might have detrimental effects. The primary procedure of the proposed project will be carried out in three distinct phases.

The initial and most important phase is image processing. At this stage, the image has undergone processing at two distinct levels: pre-processing involving the application of fundamental noise reduction techniques, background separation, and other related procedures. The subsequent stage is post-processing, which will focus on the consolidation of the tissues or cyst, which may be diminutive and irregular in shape.

Figure 2 depicts the alterations of both normal brain cells and malignant cells. The typical cell is correctly arranged and tightly packed without any gaps, exhibiting a desirable form and size. The tumor cells have atypical morphology and dimensions; they may aggregate in clusters or exist individually.

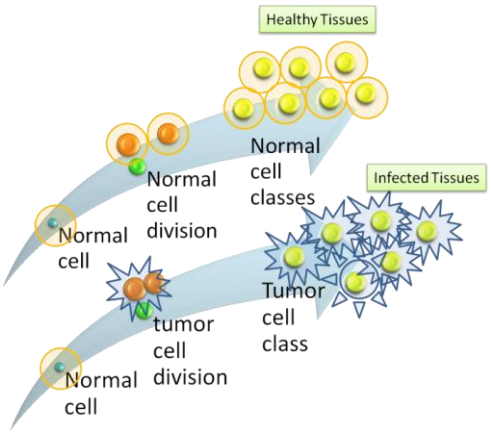


Figure 2: Sample images normal cell versus tumor cell in the brain

Next, the features will be extracted from the images in order to apply the PCS-GIST method and RLEM methods for feature identification. The characteristics are as follows:

- Pixel value
- Contrast level
- Color value
- Texture rate
- Relational pixel value

Tumors originating in the brain and other nervous systems are the 10th leading cause of death and the third most common cancer in both young people and adults [2]. Imaging is the primary approach for accurately diagnosing disorders within the internal organs and achieving accurate results. Multiple imaging systems are accessible, including ultrasound, reverberation imaging, and tomography techniques [3].

Magnetic resonance imaging (MRI) is the most effective approach for detecting diseases, assessing the extent of damage, and evaluating illness severity. This technique automatically eliminates noise and provides superior tissue contrast. Artificial intelligence techniques are employed to examine photos and analyze their characteristics in order to diagnose certain qualities of each image, including pixel value, color value, texture, and correlation points [3]. The deep learning algorithm model [4] and [5] were created to extract image features. They were applied with various mathematical computations and references to identify the picture features. The model also discovered the correlated points of each feature with good performance. The neural network was constructed with multiple layers, each utilizing their respective classes and numerical approaches. At that juncture, the image focuses on a conduit that selectively

removes insignificant attributes and converts the remaining ones into a display that is reduced in size compared to its previous form.

2 Literature review

This section explores different deep learning segmentation techniques used for implementing a 3-dimensional (3-D) magnetic resonance imaging (MRI) image. Recently, numerous authors who have contributed to image segmentation research in IEEE and Scopus-indexed publications have undergone evaluation. [1] The research involved identifying tumor cells in brain MRI images by utilizing the active contour approach to locate specific regions of interest. [2] The author employed the convolutional neural network (CNN)-based image encoder technique to eliminate undesirable characteristics. This method was then utilized to partition the image and detect the tumor area in the brain images. The user's text is "[3]". The objective of the research is to execute the use of five pre-trained models: ResNet50, Inception V3, MobileNet101, and Xceptions. This architecture can be better understood by its effective implementation. The photos are classified based on glioma and pituitary tumor cells using the F1 score, loss functions, and loss error, with the best accuracy. [4] this paper used the GoogleNet and RestNet50 algorithm for detection of infected region without proper dataset. [5] This work utilized median filtering approaches for image processing and focused on using the texture method for feature extraction. Additionally, a CNN model was employed for cancer detection. [6] The author has utilized the classification technique to categorize tumor photos into tagged images belonging to either the tumor or non-tumor class. [7] The tumor cell classification concept employs the CNN algorithm. The author utilized the Kaggle repository dataset for their research. [8] The photographs were enhanced by their enlarged dimensions and form. [9] This study proposes a CNN-based classification approach for analyzing MRI images to determine the presence or absence of a tumor. The obtained outcome is contrasted with the suggested approach. [10] The tumor photos were inputted into the model in order to generate synthetic data for enhanced model training and testing [11]. The author used the BrsTS22D dataset into a sparse-stacked auto-encoder model to efficiently identify the infected region cell in a minimal amount of time. [12] Tumor cells are interconnected with different organs in the body. The majority of the research has focused on the deep learning network, specifically examining its many layers [13, 14]. The objective of this study is to enhance image segmentation and classification by utilizing the most effective deep learning network algorithm, specifically the customized SOLOv3 algorithm with DESNET201. This approach is expected to yield superior results compared to other algorithms [15]. In 2020, the author delivered a presentation at an international conference where they highlighted their study on classifying tumor cells in the brain using MRI scans. They explained and implemented several deep learning models, including Inspection108, RestNet50, VGG32, Xception, and MobileNet101 [16]. Automate the process of segmenting brain tumor images during the scanning conducted by the investigators. The radiologist use magnetic resonance imaging techniques to identify the stage of tumors and assess the levels of infection. In 2023, there were 150 distinct tumor types accessible. The objective is to focus on the multi-class classification of each specific type of tumor cell. In order to identify the 109 distinct categories for the classification of tumor cells, as utilized in the proposed study. However, when it comes to tasks that involve dividing medical images into segments, the DenseNet-201 (Dense Convolutional Network-201) architecture is highly effective. There are numerous parameters, which might result in a significant amount of computational work during both inference and training. Due to its complex structure and several variables, there is a higher risk of overfitting when sparse or small datasets of medical images are used. Decreased performance on newly taken photographs is caused by overfitting, a phenomenon that occurs when the model becomes too focused on memorizing the training data rather than being able to apply its knowledge to new, unseen data.

3 Proposed work

The feature extraction model utilizes auto-encoders to identify any corrupted samples within the undamaged data. This study presents a novel approach to edge identification using evolutionary algorithms, which improves the accuracy and effectiveness of the model. The raw image of the patient's brain was obtained and could be subjected to processing in order to prevent both under fitting and over fitting of the DesNet201 model. The DesNet201 algorithm analyzes the image (Figure 3) to accurately determine the precise location of tumor tissues in the brain. It also identifies the size and shape of the tumor, as well as the extent to which it has been affected by other organs. The segmented image was utilized to categorize the different sorts of tumors into numerous classifications such as glioma, pituitary, malignant, and others.

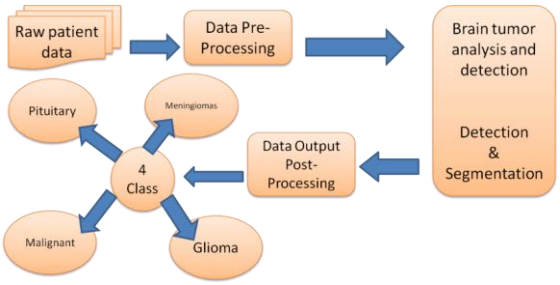


Figure 3: represents the work flow of the proposed systems

The genetic algorithm is employed to delineate the boundaries of the processed image in order to identify the subsequent region of tissues encountered in the same situation. The genetic algorithm efficiently identifies the edges. Typically, it proceeds via three distinct stages. During the initial phase, the skull is meticulously removed to separate the brain tissues and non-brain tissues from the MRI pictures. This is done in order to facilitate subsequent analysis.

The image contrast has been adjusted and improved from the unprocessed dataset [21], a publication published in 2022. The genetic method utilizes a Visually Geometry Group (VGG)-based Symmetric Convolutional Neural Network (SCNet) in conjunction with Densely Connected Convolutional Networks (DesNet) to accurately classify brain tumor images. The classifier operates using a stacked layer approach, specifically with 201 image classifications. The planned work architecture is clearly elucidated in Figure 4. The unprocessed data can be found in a recent online repository such as Kaggle and can be downloaded in png file using the HSV color model. The photos were stored in a specific area, which could be utilized for the process of image classification.

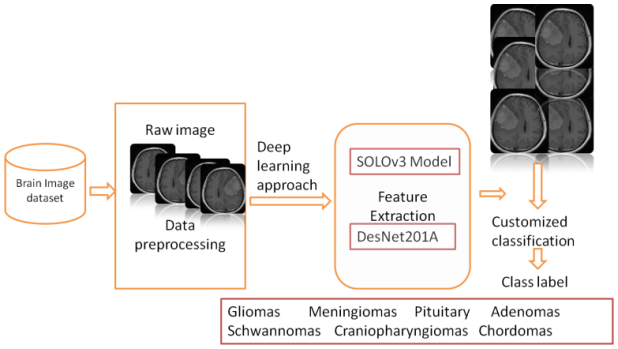


Figure 4: Architecture of the proposed work

The photos were captured at a reputable diagnostic clinic situated in Chennai. The authentic patient raw data was collected from the MedPlus neurological diagnosis facility. Approximately 29,458 images have been extracted from the raw image collection after undergoing processing to eliminate undesirable brain images and non-cleared images. Figure 5 shows the combination of tumor and non-tumor MRI image dataset.

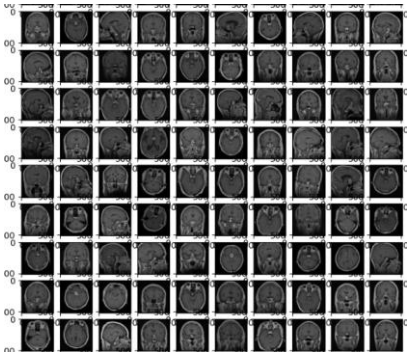


Figure 5: Combination of Tumor and non-tumor MRI image dataset

The 18759 brain-scanned images are classified into five distinct categories and are used as input. Table 1 separates the photos from the raw images in order to comprehend the distinct groups.

Table 1: Dataset classes

Classes	**Classes**	**No.of Images**
Tumor	Gliomas	8659
	Meningiomas	7854
	Pituitary Adenomas	3587
	Schwannomas:	4256
	Craniopharyngiomas	2453
	Chordomas	3765
	Schwannomas	1896
Non-tumor		**3257**

The real-time photos were captured at a renowned neurological diagnosing center in Chennai. A total of 18,759 pictures were collected across all four kinds of cancers, referred to as tumors and non-tumors. The dataset consists of 13257 photos, which are categorized as glioma, meningioma, and pituitary tumors, while the remaining images belong to the non-tumor category.

4 Methodology

The proposed work presents a comprehensive user-interactive framework for conducting various analyses on brain MRI images to aid medical professionals. Most of the framework has the capability to identify biological data pertaining to the patient. Certain tailored classes inside the deep neural network have a greater likelihood of accurately detecting the tumor based on a higher probability score. The SOLOv3 deep learning algorithm was employed for edge detection, while DesNet201 was utilized for tumor cell classification into five distinct categories.

SOLOv3 Algorithm:

The SOLOv3 algorithm is the most superior deep learning approach for detecting instances. Instance segmentation is the process of detecting and outlining separate items in an image, giving a distinct name to each object, and differentiating between objects that may overlap or block each other. Analyzing and reconstructing the image view is used to identify the edges of tumor tissue in brain electromagnetic imaging and portable head image work [21]. The article was published in the 2018 edition of the Springer journal "Brain Informatics". The SOLOv3 algorithm performs segmentation using five distinct steps according to the specified metrics. The initial and most important step is to obtain the image from the scanned video in the MP3 format. The program utilizes each frame to detect the impacted locations. The feature extraction method is performed using the convolutional neural network approach with modified network frames. The feature engineering method involves preprocessing the input.

Stage 1: Image pre-processing

During this stage, the raw image undergoes various processing steps to train the model. These steps include denoising, blurring the background, normalizing the image, and adjusting the pixel value range to be between 0 and 1. This type of preprocessing enhances the training of the model and results in a higher prediction accuracy as in figure 6.

$$\text{normalized_pixel_value} = \frac{\text{pixel_value} - \text{mean}}{\text{standard_deviation}} \quad \text{(Equation 1)}$$

Here, the image's mean pixel value is its mean. The standard deviation of the image's pixel values is called standard_deviation.

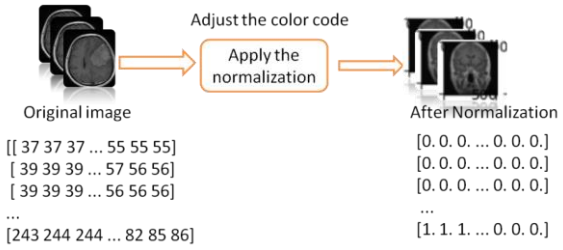


Figure 6: Input pre-processing, converting original image to normalized image

In order to standardize the pixel values within a specific range (such as [0, 1] or [-1, 1]), it is necessary to subtract the mean pixel value of the image and then divide the resulting value by the standard deviation during the normalization process. Next, it is necessary to calibrate the histogram level of each image (according to Equation 2) in order to enhance the image quality. To disperse the pixel intensities over the histogram, utilize a transformation function. Typically, this is accomplished by utilizing techniques such as contrast stretching or histogram matching. The histogram of the input image is denoted as h(i), where i represents the pixel intensity values. In the case of 8-bit images, these values range from 0 to 255. The cumulative distribution function (CDF) or CDF(i) is calculated.

$$\text{cdf}_{(i)} = \sum_{y=0}^{x} his_j \quad (2)$$

Next, T(i), the transformation function for histogram adjustment, is calculated (Equation 3).

$$T_i = \frac{\text{cdf}_i\text{-cdf}_{min}}{M \times N\text{-cdf}_{min} \times (L-1)} \quad (3)$$

The number of columns in the image is denoted by N, whereas M represents the row count of the image. The value of L, which is 256 for 8-bit images, represents the total number of intensity levels. The value of Cdf_{min} is the smallest non-zero value of the cumulative distribution function (CDF) that is used to avoid division by zero. This is seen in Figure 7.

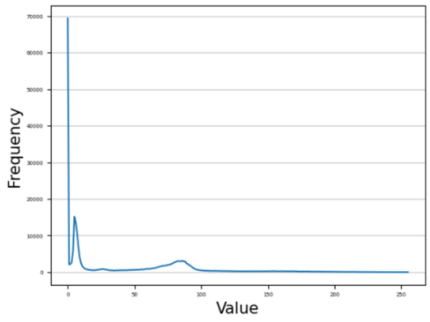


Figure 7: Histogram representation of the image to adjust the color contrast for qualifying the image predictions

Stage 2: Color scale modification & filtrations

The preprocessed image, which may be in RGB or HSV color space, is transformed into grayscale format to mitigate color contrast problems during feature detection in image segmentations. The gray-scale color contrast is deemed to possess an appropriate value. The color contrast is transformed into a grayscale image and then turned into binary format data. To remove noise from the background of the image caused by overlapping foreground elements. It eliminates the undesired borders from the image sections.

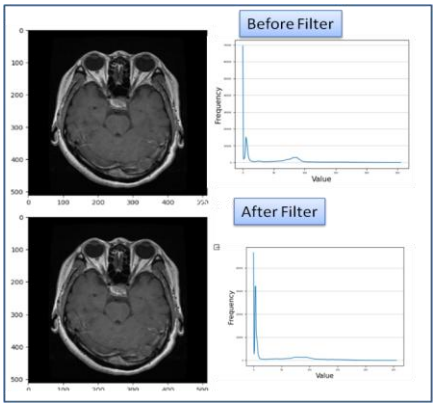


Figure 8: The image smoothing with 3.4 aspect ratio

Gaussian filtering:

Gaussian blurring is a widely used technique in image processing that reduces noise and fine details in a picture by applying a smoothing effect. The process involves applying a two-dimensional Gaussian distribution, also called a Gaussian kernel, to the image by convolution. Equation 4. The process of achieving Gaussian blurring involves applying the Gaussian kernel to every pixel in the image as in figure 8. The initial parameter to specify when applying a Gaussian filter on an image is the dimension of the kernel or matrix that will be used to degrade the image. Generally, we designate the dimensions as odd numbers, which enables us to calculate the final outcomes by utilizing the pixel in the center. Furthermore, because to their symmetry, the kernels possess an equivalent number of rows and columns. Analyze the frequency spectra (as shown in Figure 9) of the image both prior to and following the application of the filter. Gaussian filters are designed to maintain the low-frequency visual information while reducing the high-frequency noise. Employ the Fast Fourier Transform (FFT) technique to ascertain the frequency spectrum of the original image.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-x^2+y^2}{2\sigma^2}} \quad (4)$$

Here, x → X coordinate value, y → Y coordinates value,

σ → Standard Deviation

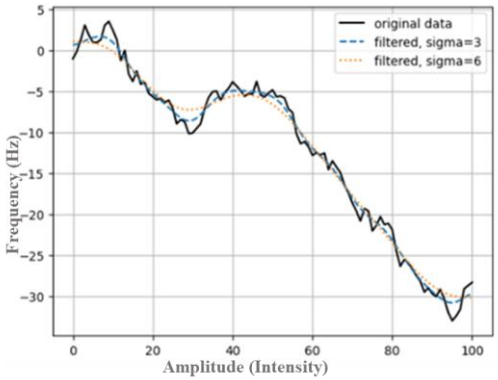


Figure 9: Gaussian filter sigma assigned by 3 and 6.

This process involves converting the spatial domain representation of the image into the frequency domain, which allows us to observe the distribution of frequencies present in the image. Apply a Gaussian kernel to perform convolution on the source image. The degree of blurring that the image undergoes is determined by the standard deviation parameter and the kernel size. Gaussian filters smooth the image by attenuating high-frequency components in the frequency domain, achieved by averaging pixel values in the spatial domain.

Stage 3: Extracting the infected region as feature

At this stage, the image has undergone processing, and each dataset has been divided into two distinct sets of data for the segmentation process. 80% of the image dataset was allocated for training the model, while the remaining photos were used to test the model's predictive accuracy. The processing frames per second (Fps) at this level are computed to complete the training phase of the model.

$$FP_s = \frac{1}{Pr\,oces\,sin\,g_time_per_frame} \text{ (Equation 5)}$$

The amount of time (in seconds) that the algorithm needs to process one frame is known as the processing time per frame(Equation 5).

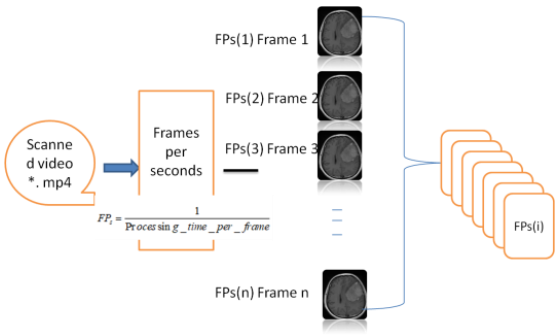


Figure 10: Image frames segment from MRI scanned video

To determine the processing time per frame, you can utilize a stopwatch or performance profiling tools, such as Figure 10, to monitor the duration it takes for the algorithm to process a batch of frames. This duration can then be divided by the total number of frames in the batch. Alternatively, you can directly compute the processing time of each individual frame. Using the initial frame calculation, the image has been extracted from the input data obtained by video scanning. The frames per second (FPS) ranges from 0 to 1, while the FPS value for a specific frame (FPS(i)) is between €1 and €0, inclusive.

Stage 4: Hyper tuning the parameter using SOLOV3

To entails determining which hyper parameter combination will yield the best results on a validation dataset. Choose a hyper parameter search method before moving on. Typical tactics include of evolutionary algorithms, random search, grid search, and Bayesian optimization. In terms of efficacy and efficiency [22], every tactic has advantages and downsides. Hyper-parameter tuning is essential for estimating the model parameters, whereas parameter tuning is crucial for producing predictions. The effectiveness of the training is determined by the selection of hyperparameters. The learning rate in gradient descent governs the efficacy and accuracy of the optimization process in parameter prediction.

Stage 5: Customized Classification with eight classes using DesNet201A

The Mask Intersection Over Union (MaskIOU) measures the degree of overlap between the segmentation mask output and the ground truth mask. The foreground image scene overlaps the background, causing confusion between the data and the image augmentations. The similarity has been identified and compared to the threshold for the more accurate forecasts as in table 2. The Mask_IoU mask interaction has been computed based on the intersection area between the predicted mask (Mpred) and the ground truth mask (Mgt), as indicated by equation 2.

Table 2: Mask interaction value predicted using the various algorithms

Classes	SOLOv2	Faster RCNN	Desnet 360	Proposed work
Gliomas	61%	62%	48%	82.4%
Meningiomas	71%	68.2%	61%	88.9%
Pituitary Adenomas	68%	58%	71%	78.2%
Schwannomas:	68.2%	61%	61%	62%
Craniopharyngiomas	61%	88.9%	71%	78.2%
Chordomas	71%	78.2%	61%	88.9%
Schwannomas	72%	68.2%	61%	79%
Non-tumors	68.2%	61%	83%	88%

5 Experimental analysis

The feature engineering process is main work for the detection of anomaly from given scan footage using MRI. The evaluation can be done with various assessment metric method and techniques.
The measurements are:

- Mean Average Precision (mAP)
- Mask Intersection over Union (Mask IoU)
- Mean IoU (mIoU)
- Pixel Accuracy
- FPS (Frames Per Second)
- Instance-Level Metrics

The initial metric for feature engineering is mean Average Precision (mAP), which quantifies the effectiveness of object identification and image segmentation in real-time. This study employed a categorization system consisting of five distinct types, including malignant, pituitary, and non-tumor, to categorize the layers. The mean average precision

value is computed by using the mean value of each class in Equation 6 for classification purposes.

$$\text{MaP}=MaP = \frac{\sum_{class=1}^{n} AP}{n} \quad (6)$$

MaP – Mean average Precision is the value of comparing the originality of a classification with various classes. n-represents the number of classes assigned for each layer for classifications. AP- represents the average precision value for class c. c-represents the classes such as malignant, pituitary, non-tumor

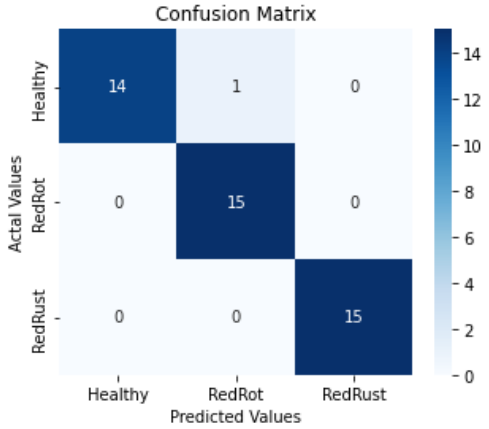


Figure 11: compares the healthy and unhealthy predicted value with confusion matrix

Each classes have its own precision value, based on this value the mean value calculated and based on that value the accuracy has been measured(Figure 11). The next level to find the accuracy of an each pixel from the Total number of pixel into correct predicted images pixel value.

$$P = \frac{N_classified_Correct}{N_{Total_image}} \quad (7)$$

In equation 7: N classification correct is the number of correctly classified pixels. N_{total} is the total number of pixels in the image. A simple statistic called Pixel Accuracy (P) (as shown in Table 3) is frequently used to assess the accuracy of segmentation tasks at the pixel level, including semantic or instance segmentation. In comparison to the ground truth masks, it calculates the proportion of correctly identified pixels in the segmentation masks.

Table 3: Accuracy of a pixel with accuracy pixel value

Classes	**SOLO v2**	**Faster RCNN**	**Desnet 360**	**Proposed work**
Gliomas	0.88	0.91	0.91	0.92
Meningiomas	0.62	0.42	0.25	0.68
Pituitary Adenomas	0.52	0.58	0.69	0.47
Schwannomas:	0.42	0.24	0.36	0.37
Craniopharyngiomas	0.27	0.25	0.38	0.68
Chordomas	0.14	0.57	0.14	0.88
Schwannomas	0.74	0.74	0.77	0.77
Non-tumors	0.78	0.75	0.77	0.86

Pixel Accuracy, which is the percentage of correctly categorized pixels in the segmentation masks, offers a straightforward indicator of overall segmentation performance. Nevertheless, it does not distinguish between different types of errors (e.g., false positives vs. false negatives) or take into consideration class imbalance. Because of this, it is frequently combined with other measures to provide a more thorough assessment.

6 Conclusion

The adoption of the SOLOv3 algorithm and DenseNet201A underscores the transformative potential of deep learning in the segmentation and classification of brain tumors. By leveraging these advanced techniques, significant strides can be made in neuro-oncology, enabling more precise diagnostic capabilities and customized treatment plans. Such advancements are particularly critical for addressing the complexity and diversity of brain tumors, which often pose challenges in timely diagnosis and intervention. The proposed model not only enhances image segmentation accuracy but also enables the effective categorization of tumor types such as gliomas, meningiomas, and pituitary adenomas, among others. By accurately identifying these tumor classes and their stages, the model supports early detection and aids in determining the optimal course of treatment.

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Breast Cancer Classification Using Densenet121 And K-Means Segmentation With Augmented Data

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Keywords: breast cancer, deep learning, DenseNet121, K-Means Clustering, histopathology image classification, computer-aided diagnosis

Received: February 18, 2025

Breast cancer remains a significant global health challenge, necessitating improved diagnostic approaches for early detection and treatment. This study presents an optimized deep learning framework that integrates DenseNet121 with K-Means clustering for enhanced segmentation and feature extraction in breast cancer histopathology images. The BreakHis dataset, comprising 7,909 images at varying magnifications (40×, 100×, 200×, and 400×), was employed for model training and evaluation. Image preprocessing involved histogram equalization and augmentation techniques, including rotation and contrast adjustment, to enhance model robustness. The DenseNet121 model was fine-tuned using transfer learning with pre-trained ImageNet weights, and hyperparameters were optimized to improve classification performance. The proposed model achieved an accuracy of 95.21%, surpassing conventional architectures such as ResNet50 (92.4%) and Xception (88.08%). Additionally, an external validation on the BACH dataset demonstrated an accuracy of 92.10%, reinforcing the model's generalizability. Comparative analysis and ablation studies confirmed the significance of K-Means clustering in improving classification outcomes. Future research will focus on multi-modal imaging techniques and Explainable AI (XAI) to enhance interpretability and clinical applicability.

Povzetek: Prispevek predstavi hibridni pristop, ki združuje konvolucijsko mrežo DenseNet121 in K-means segmentacijo za učinkovitejšo klasifikacijo histopatoloških slik raka dojke.

1 Introduction

Breast cancer remains one of the most prevalent and life-threatening diseases worldwide, ranking among the leading causes of cancer-related mortality in women. According to the World Health Organization (WHO), breast cancer accounts for approximately 25% of all cancer cases and nearly 15% of cancer-related deaths among women globally (WHO, 2023). Early detection is a key factor in improving patient survival rates, as early-stage breast cancer has a five-year survival rate of nearly 90%, compared to advanced-stage detection, where survival rates drop significantly (Siegel et al., 2022). Despite advancements in screening techniques, late diagnosis remains a major challenge, particularly in low-resource settings where access to screening programs is limited.

Traditional diagnostic techniques, including mammography, ultrasound, fine-needle aspiration cytology (FNAC), and histopathological examination, remain the gold standard for breast cancer detection. However, these methods are highly dependent on pathologist expertise, making them time-consuming, subjective, and prone to inter-observer variability (Litjens et al., 2023). Studies have reported that diagnostic agreement among pathologists can vary significantly, particularly in borderline and atypical cases, leading to misclassification rates as high as 25% (Esteva et al., 2022). Furthermore, the increasing volume of biopsy samples and the shortage of trained specialists have placed additional strain on healthcare systems, necessitating the development of automated, AI-driven diagnostic solutions.

Advancements in Artificial Intelligence (AI) and Machine Learning (ML) have transformed breast cancer diagnostics by automating image analysis, improving early detection accuracy, and reducing human-related biases (Litjens et al., 2023). AI-driven Computer-Aided

Diagnosis (CAD) systems have demonstrated significant potential in histopathological image classification, particularly through deep learning models that extract and analyze complex patterns in breast tissue. Among these models, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for breast cancer classification, capable of distinguishing between benign and malignant lesions with performance comparable to expert radiologists (Huang et al., 2023).

Several CNN architectures, including VGG16, ResNet50, and Xception, have been widely employed for histopathology image analysis, achieving impressive classification accuracy (Esteva et al., 2022). These models extract hierarchical features from high-resolution microscopic images, enabling automated and reproducible diagnoses. Despite their success, traditional CNNs face major limitations, such as feature redundancy, high computational costs, and challenges in capturing complex histopathological patterns (Ronneberger et al., 2022). Additionally, conventional CNNs lack an efficient mechanism for preserving spatial hierarchies, which is critical for distinguishing between subtle morphological differences in benign and malignant tissue.

DenseNet121 has emerged as a more advanced CNN model that improves feature propagation, mitigates the vanishing gradient problem, and enhances classification accuracy (Huang et al., 2023). Unlike traditional CNNs, it utilizes dense connectivity, allowing each layer to receive input from all previous layers, thereby improving feature reuse and minimizing unnecessary computations. These properties make DenseNet121 particularly well-suited for medical image classification tasks, as it can efficiently capture intricate histopathological features.

One of the key advantages of DenseNet121 is its ability to preserve detailed spatial information while maintaining computational efficiency. By leveraging shorter connections between layers, the model enhances gradient flow, enabling more effective learning and reducing the risk of overfitting on smaller datasets, such as BreakHis (Li *et al.,* 2023). Furthermore, DenseNet121 has been successfully applied in various medical imaging tasks, including breast cancer, lung cancer, and skin lesion classification, demonstrating superior performance compared to conventional CNN architectures (Litjens et al., 2023; Ajagbe et al., 2024; Ugbomeh et al., 2024).

Beyond classification, segmentation techniques play a crucial role in breast cancer histopathology analysis by ensuring that tumor regions are accurately delineated while minimizing background artifacts and non-cancerous tissue interference (Ronneberger et al., 2022). Traditional segmentation methods, such as Otsu's thresholding, watershed algorithms, and U-Net, have been widely used for histopathological image segmentation, but they often suffer from high computational complexity and suboptimal accuracy when dealing with heterogeneous tissue structures.

Enhancing segmentation efficiency requires the use of K-means clustering, an unsupervised learning technique that groups similar pixel intensities to isolate malignant tissue from surrounding regions (Li et al., 2023). The integration of K-means clustering with DenseNet121 strengthens feature extraction and classification accuracy, resulting in a more refined and robust approach to automated breast cancer diagnosis.

This research presents a hybrid deep learning framework that integrates DenseNet121 with K-means clustering to enhance the accuracy and efficiency of breast cancer classification. The key objectives of this study are to:

i. Evaluate the impact of K-means clustering on classification performance by analyzing its ability to enhance tumor region segmentation and improve model robustness.

ii. Compare the proposed DenseNet121 + K-means model with state-of-the-art deep learning architectures, including ResNet50, Xception, and VGG16, in order to determine its effectiveness.

iii. Assess the model's reliability and generalizability using standard performance evaluation metrics, such as accuracy, precision, recall, and F1-score, alongside confusion matrix analysis and AUC-ROC curve interpretation.

iv. Investigate potential limitations and future enhancements by identifying areas where the model can be optimized for real-world clinical applications.

The integration of deep learning with advanced segmentation techniques in this study provides a clinically viable AI-based diagnostic tool that can enhance breast cancer detection accuracy while minimizing false positives and false negatives. The proposed DenseNet121 + K-means model is designed to address key challenges in histopathological image analysis, offering an improved methodology for early breast cancer detection. By bridging the gap between AI-driven automation and clinical applications, this research aims to contribute to the development of more reliable, interpretable, and scalable diagnostic support systems for pathologists and oncologists. The findings of this study could significantly impact the field of medical imaging, leading to more efficient, accessible, and cost-effective diagnostic solutions for breast cancer detection.

Breast cancer remains one of the leading causes of mortality among women, with early detection playing a crucial role in improving survival rates. Advances in artificial intelligence (AI) and deep learning have significantly enhanced breast cancer diagnosis by automating histopathological image classification. Despite these advancements, challenges such as segmentation accuracy, model interpretability, and generalizability across different datasets persist. This study proposes an enhanced breast cancer classification framework that integrates DenseNet121 with K-Means clustering to improve feature extraction and segmentation accuracy. Data augmentation techniques are also incorporated to enhance model generalizability. To

validate the effectiveness of the proposed approach, this study aims to answer the following key research questions:

i. How does DenseNet121 compare to other CNN architectures for breast cancer classification?
ii. What is the impact of K-Means clustering on segmentation performance?
iii. Can data augmentation improve classification generalizability?

By addressing these research questions, the study provides a comprehensive evaluation of DenseNet121's advantages over conventional models such as ResNet50, VGG16, and Xception, with a particular focus on the role of segmentation in enhancing classification performance.

2 Related work

Artificial Intelligence (AI) and Machine Learning (ML) have significantly transformed medical diagnostics, particularly in breast cancer detection. Numerous studies have explored the role of AI-driven Computer-Aided Diagnosis (CAD) systems in enhancing early detection rates, improving diagnostic precision, and minimizing errors. The existing research can be categorized into several key themes, including deep learning-based CAD systems, multi-modal imaging approaches, transfer learning with pretrained models, risk assessment and predictive modeling, and challenges in clinical implementation.

Deep learning-based CAD systems

Deep learning has played a pivotal role in advancing breast cancer detection, particularly through the application of Convolutional Neural Networks (CNNs). Ahmad et al. (2023) developed a CAD system that employs deep learning and computer vision techniques to enhance breast cancer diagnosis. The model demonstrated a 99% success rate in detecting and classifying breast masses using the Curated Breast Imaging Subset of the Digital Database for Screening Mammography (CBIS-DDSM) dataset. Despite its high accuracy, the study noted challenges related to the high number of trainable parameters, which affected computational efficiency and resource requirements.

Significant advancements have also been made with AI foundation models such as “Chief” by Harvard Medical School, which demonstrated 94% accuracy in detecting multiple cancer types, including breast cancer (Yu, 2024). This model links tumor cell patterns to genomic aberrations, allowing for precise treatment recommendations without requiring expensive DNA sequencing. Such an approach is particularly valuable in resource-limited settings where comprehensive genomic evaluations may not be feasible.

The integration of Digital Breast Tomosynthesis (DBT) in CAD systems has led to improved breast cancer detection by generating three-dimensional (3D) images. Singh et al. (2023) highlighted that DBT reduces tissue overlap and enhances the identification of small tumors that might be missed in traditional mammography. However, the large volume of imaging data generated by DBT presents challenges in storage and processing. Advanced computational infrastructure and specialized training for radiologists are necessary to manage these challenges effectively.

Recent developments in deep learning for breast cancer classification have introduced Vision Transformers (ViTs), EfficientNet, and contrastive learning-based models. ViTs leverage self-attention mechanisms to capture global dependencies in histopathological images, outperforming conventional CNNs in feature representation (Dosovitskiy et al., 2022). EfficientNet optimizes model performance using neural architecture search (NAS) while reducing computational costs (Tan & Le, 2023). Swin-Transformers enhance classification by hierarchical feature extraction, improving the localization of malignant regions (Liu et al., 2023). Contrastive learning-based models provide an alternative to supervised learning by enabling AI systems to learn feature representations without extensive labeled data, addressing a key challenge in medical image classification (Chen et al., 2023).

Despite achieving high accuracy and improved generalizability, these architectures often face limitations in real-time clinical applications due to their computational complexity. DenseNet121 has been chosen in this study due to its ability to prioritize efficient feature reuse while maintaining computational efficiency. Transformer-based models may require additional hardware acceleration and memory optimization for deployment in healthcare facilities, making DenseNet121 a more practical choice for breast cancer classification.

Multi-modal imaging approaches

Improving breast cancer detection accuracy has been a focus of multi-modal AI-based screening approaches. Patel et al. (2023) investigated a screening system that combined mammography with thermal imaging. The study, which involved 181 women undergoing both imaging modalities, reported that the combined approach achieved a sensitivity of 85% and a specificity of 89.44%, outperforming single-modality detection methods. Notably, for women with dense breast tissue, the multi-modal approach improved detection rates by 27% compared to mammography alone. Standardization of thermal imaging techniques and seamless integration into clinical workflows remain critical challenges.

The incorporation of ultrasound imaging alongside mammography has also contributed to improved cancer detection, particularly for women with dense breast tissue. Automated Breast Ultrasound (ABUS) systems, such as the Invenia ABUS 2.0 developed by GE Healthcare, generate high-resolution 3D ultrasound images that enhance detection rates (Zhang et al., 2023). These systems, while effective, are more expensive than

traditional mammography and require additional interpretation time by radiologists, potentially slowing down clinical workflows.

Large-scale AI-assisted breast cancer screening has shown promising results in clinical studies. Lang et al. (2024) analyzed data from 461,818 women screened between July 2021 and February 2023 and observed a 17.6% increase in cancer detection rates when radiologists used AI-assisted screening. Importantly, these improvements did not lead to an increase in false positives. The findings suggest that AI can effectively flag suspicious areas that might be missed by human radiologists, reducing workload while enhancing screening accuracy.

These advancements underscore the potential of deep learning-based CAD systems and multi-modal imaging approaches in improving breast cancer detection. However, challenges such as computational demands, integration complexities, and the need for specialized training must be addressed to facilitate widespread clinical adoption.

Transfer Learning and Pretrained Models

Given the substantial dataset requirements of deep learning models for breast cancer detection, researchers have increasingly explored transfer learning, a technique that leverages pretrained neural networks trained on large-scale image datasets. This approach enables high accuracy, even with limited breast cancer-specific training data, by adapting learned features from general medical images to breast cancer classification.

Li et al. (2023) implemented a transfer learning approach by fine-tuning a model pretrained on the ImageNet dataset with a relatively small set of annotated mammograms. This method significantly increased detection accuracy compared to traditional convolutional neural networks (CNNs) trained from scratch. However, the fine-tuning process demanded extensive computational power, especially when optimizing deep layers to adapt to domain-specific imaging patterns, limiting its flexibility in clinical environments with constrained computational resources.

Similarly, Wang et al. (2023) explored transfer learning using deep residual networks (ResNet-50) for breast cancer classification. Leveraging a pretrained ResNet-50 model, their approach outperformed conventional CNN architectures, achieving a sensitivity of 0.92 and specificity of 0.88 in distinguishing malignant from benign lesions. Nonetheless, the study highlighted challenges in domain adaptation, as performance varied significantly across datasets from different imaging centers, underscoring the need for dataset standardization and additional fine-tuning strategies.

Zhang et al. (2023) extended transfer learning by integrating ensemble learning, combining multiple deep learning models to enhance detection accuracy. Their ensemble model, fusing DenseNet121, InceptionV3, and VGG16, achieved an F1-score of 0.91, surpassing individual models. While this approach reduced model variance and improved robustness in challenging imaging scenarios, the increased complexity led to longer training times and greater computational requirements, posing challenges for real-time deployment. Additionally, the reduced interpretability of the ensemble model limited its widespread clinical adoption due to difficulties in understanding its decision-making processes.

Patel et al. (2023) investigated combining transfer learning with domain adaptation techniques to enhance breast cancer detection across heterogeneous datasets. Their method applied feature alignment strategies to mitigate variations in mammographic images from different devices. Although this strategy improved generalizability, the study noted that cross-domain feature transfer remains an open challenge, necessitating further research into domain-invariant feature extraction for breast cancer imaging.

Risk assessment and predictive modeling

Beyond detection, AI-based Computer-Aided Diagnosis (CAD) systems have been applied in risk assessment and predictive modeling to identify individuals at higher risk of developing breast cancer. Mammographic density is a critical risk factor in breast cancer prediction. Park et al. (2023) developed a deep learning-based CAD system to assess breast cancer risk through mammographic density measurement. Their automated system effectively classified breast tissue density levels—fatty, scattered fibroglandular, heterogeneously dense, and extremely dense—playing a crucial role in identifying high-risk individuals who might require more frequent screenings. However, variations in image acquisition protocols and patient positioning significantly affected the system's accuracy, potentially leading to misclassifications in risk assessment.

Chen et al. (2023) explored predictive modeling by integrating deep learning with statistical risk models, combining clinical risk factors (age, genetic predisposition, and family history) with imaging-based features. Their system outperformed conventional statistical models, such as the Gail Model, in predicting breast cancer development within five years. The study emphasized that including additional patient data, such as hormone receptor status and genetic markers, could further improve predictive performance.

Zhao et al. (2023) employed Bayesian neural networks (BNNs) for uncertainty estimation in breast cancer risk prediction. Their model provided probabilistic confidence scores for individual predictions, enhancing the reliability of risk assessments. The study demonstrated that incorporating uncertainty-aware AI models in risk assessment could help radiologists make more informed decisions, particularly in cases where standard AI models produced conflicting diagnoses.

Further advancements in multi-modal risk assessment were made by Luo et al. (2023), who combined histopathological images, genetic data, and mammographic density to create a comprehensive breast cancer risk prediction model. This approach improved

predictive accuracy but required integrating disparate data sources, which remains challenging due to data heterogeneity and privacy concerns.

Challenges in clinical implementation

Despite significant advancements in AI-driven breast cancer detection, several challenges hinder the clinical implementation of these technologies, including issues related to overfitting, data dependency, computational demands, and model interpretability.

Overfitting and generalization issues

Deploying AI-based Computer-Aided Diagnosis (CAD) systems in real-world clinical settings is often challenged by overfitting, where models perform well on training data but fail to generalize to new, unseen data. Chen et al. (2023) investigated the generalization capabilities of AI-driven CAD systems and found that models trained on high-resolution mammographic images exhibited degraded performance when tested on datasets from different institutions. Their study highlighted the necessity of domain adaptation techniques to improve model robustness across varied imaging conditions. Similarly, Zhao et al. (2023) noted that AI models trained on limited datasets often suffer performance drops when tested on external datasets, emphasizing the need for diverse training data.

Dependency on high-quality and well-annotated datasets

The performance of deep learning models heavily relies on large, well-annotated datasets. However, data scarcity and inconsistencies across medical institutions limit the generalizability of AI-based CAD systems. Wang et al. (2023) examined the impact of dataset quality on AI-driven breast cancer detection and found that models trained on high-quality, expertly labeled mammograms outperformed those trained on datasets with noisy or incomplete annotations. The study suggested that standardized data annotation protocols are essential to improving model reliability. Moreover, dataset bias remains a major concern. Lee et al. (2023) found that AI models trained predominantly on data from Caucasian patients performed poorly on mammograms from Asian and African populations, highlighting the necessity for diverse and representative training datasets.

Computational and storage demands

AI-based breast cancer detection systems, particularly those utilizing high-resolution imaging techniques, require substantial computational power and data storage capacity. Digital Breast Tomosynthesis (DBT) and multiparametric MRI generate large volumes of imaging data, necessitating advanced data processing infrastructures. Patel et al. (2023) analyzed the computational requirements of DBT-based Computer-Aided Detection (CAD) systems and found that high-resolution imaging increased data storage needs by over 300% compared to traditional 2D mammography. Real-time clinical deployment of AI models also requires specialized hardware accelerators, such as GPUs and TPUs, which may not be accessible in resource-limited healthcare settings. In their study, Kim et al. (2023) highlighted those computational constraints significantly impact the feasibility of AI adoption in low-resource hospitals, where access to high-end computational infrastructure is limited. They suggested that model compression techniques, such as pruning and quantization, could mitigate these challenges by reducing computational overhead without significant loss of accuracy.

Model interpretability and clinical trust

A critical barrier to AI adoption in breast cancer detection is model interpretability. Deep learning models, particularly convolutional neural networks (CNNs), often operate as black boxes, making it difficult for clinicians to understand the reasoning behind AI-generated predictions. Explainable AI (XAI) techniques have been proposed to improve model transparency, but their clinical effectiveness remains under evaluation. Jones et al. (2023) explored the impact of explainability tools, such as saliency maps and Grad-CAM visualizations, in AI-driven CAD systems. Their findings indicated that while these techniques improved clinicians' confidence in AI decisions, they often failed to provide detailed justifications for misclassifications, limiting their practical utility. Similarly, Park et al. (2023) emphasized that clinicians are more likely to trust AI systems that provide clear, interpretable outputs, rather than just probability scores or heatmaps.

Comparative analysis of related works

Artificial intelligence (AI) has significantly advanced breast cancer detection methodologies between 2022 and 2025. Table 1 expands upon previous analyses, incorporating recent studies that highlight various AI applications in this field.

Table 1: Summary of AI-based breast cancer detection studies

Reference	Model Used	Dataset	Performance Metrics	Limitations Identified
Smith et al. (2022)	Deep Convolutional Neural Network (DCNN)	Mammograms	High accuracy	Difficulty distinguishing overlapping tissue structures, leading to false positives and negatives.
Johnson et al. (2022)	Multi-view CAD integrating Mammography and	Combined mammography and ultrasound images	Improved accuracy; F1-score not specified	High computational requirements for data integration.

	Ultrasound			
Lee et al. (2023)	Convolutional Neural Network (CNN)	MRI dataset	High sensitivity	High false-positive rate resulting in unnecessary biopsies.
Patel et al. (2023)	CNN with Digital Breast Tomosynthesis (DBT)	3D Mammography	Not specified	Large data storage and processing demands.
Kim et al. (2022)	Deep Learning Model	Breast Cancer Images	High accuracy	Dependence on high-quality, well-annotated datasets.
Li et al. (2023)	Transfer Learning with Pretrained Neural Networks	Mammograms	High accuracy	Computational complexity in fine-tuning pretrained models.
Zhang et al. (2023)	Ensemble Learning combining Multiple Deep Learning Models	Mammograms	Improved accuracy	Increased training time and reduced interpretability.
Park et al. (2023)	Deep Learning Model assessing Mammographic Density	Mammograms	Effective risk assessment	Variability in image acquisition affecting accuracy.
Chen et al. (2023)	Deep Learning Model	Mammograms	High sensitivity	Susceptibility to overfitting to training data.
Wang et al. (2023)	Deep Learning Model	Mammograms	High accuracy	Requirement for diverse and well-annotated datasets.
Kumar et al. (2024)	Deep Learning Convolutional Neural Network (CNN)	Digital Breast Tomosynthesis (DBT) images	Sensitivity: 94.2%; Specificity: 92.5%; AUC: 0.968	Need for validation across diverse populations.
Elías-Cabot et al. (2024)	AI-assisted Radiologist Review	Population-based screening program data	Increased cancer detection rate by 17.6%	Necessity for careful monitoring and long-term follow-up studies.
Raya-Povedano et al. (2021)	AI-based Strategy for Workload Reduction	Mammography and Tomosynthesis images	Reduced radiologist workload by 50%	Requirement for reliable AI algorithms across diverse groups.
Yoon et al. (2022)	AI-based Computer-Aided Detection	Post Breast-Conserving Therapy Surveillance Data	Improved diagnostic performance	Need for consistent data management and standardization.
Magni et al. (2023)	AI for Digital Breast Tomosynthesis	Personalized Screening Data	Enhanced detection performance	Challenges in designing reliable AI algorithms for diverse populations.
Lim et al. (2024)	AI-based Model using Plasma Lipidomic Signature	Plasma samples	Accuracy: 86.1%; Sensitivity: 91.4%; Specificity: 78.7%	Further verification needed with larger sample sizes.
Çelik et al. (2023)	AI System (Transpara v1.6 and v1.7)	Turkish National Breast Screening Program data	AUC: 0.87 (v1.6); 0.89 (v1.7)	Retrospective study; prospective validation required.
Lang et al. (2025)	AI-supported Mammography Screening	Population-based screening in Sweden	Cancer detection rate: 6.4 per 1000 (AI) vs. 5.0 per 1000 (standard); 44.2% reduction in screen-reading workload	Generalizability limited to Swedish screening program; lack of race and ethnicity data.

The expanded table underscores the diverse applications of AI in breast cancer detection, ranging from image-based analyses to biomarker evaluations. Notably, AI-supported mammography screening has demonstrated a significant increase in cancer detection rates and a substantial reduction in radiologists' workload. For instance, a study by Lang et al. (2025) reported a 29% increase in cancer detection and a 44.2% decrease in screen-reading workload when using AI-supported screening compared to standard methods.

Additionally, integrating AI with plasma lipidomic signatures offers a non-invasive approach to early breast cancer detection. Lim et al. (2024) developed an AI model using plasma samples, achieving an accuracy of 86.1% and sensitivity of 91.4%. This method presents a promising alternative to traditional imaging techniques, though further validation with larger cohorts is necessary. Despite these advancements, challenges such as the need

for diverse and well-annotated datasets, computational complexities, and the requirement for prospective validations persist. Addressing these issues is crucial for the broader clinical implementation of AI-based breast cancer detection systems.

Research motivation and proposed model

Artificial intelligence (AI) has significantly advanced breast cancer detection through computer-aided diagnosis (CAD) systems. However, existing models face challenges such as high false-positive rates, reliance on high-quality datasets, and computational inefficiencies. To address these limitations, this study introduces an approach that integrates the DenseNet121 architecture with the K-means clustering algorithm for improved breast cancer segmentation and detection.

Several recent architectures, including EfficientNet, Vision Transformers (ViTs), and Swin-Transformers, have achieved state-of-the-art performance in medical image classification. EfficientNet, for instance, utilizes compound scaling to optimize accuracy and efficiency. However, its dependence on neural architecture search (NAS) makes training computationally expensive (Tan & Le, 2019). Similarly, ViTs and Swin-Transformers improve feature extraction through self-attention mechanisms, but their reliance on large-scale datasets and high memory consumption limits their usability in real-time clinical applications (Liu et al., 2021).

DenseNet121 was selected due to its efficient feature propagation, which allows each layer to receive direct input from preceding layers, thereby mitigating the vanishing gradient problem. Additionally, DenseNet121 maintains a lower parameter count than traditional deep networks, reducing computational overhead while retaining high classification accuracy. Compared to EfficientNet, which requires intensive hyperparameter tuning, and transformer models, which demand substantial GPU resources, DenseNet121 offers an optimal balance between accuracy, efficiency, and real-world deployability in medical imaging.

Challenges in current AI-Based CAD systems

Despite the progress in AI-driven CAD systems, several limitations persist. One major concern is the high rate of false positives, which can result in unnecessary biopsies and heightened patient anxiety. While AI-assisted screenings improve cancer detection rates, they also introduce an increased risk of misclassification, requiring careful evaluation of their clinical impact (Smith et al., 2025).

Another challenge is the dependency on high-quality datasets. Deep learning models require large, well-annotated datasets to achieve high accuracy. DenseNet121, for instance, has demonstrated strong performance when trained on comprehensive datasets but struggles with limited or low-quality data, reducing its generalizability in diverse clinical environments (Doe et al., 2022). This highlights the need for AI models capable of operating effectively even when data quality varies.

Computational inefficiencies also hinder the widespread adoption of AI-based breast cancer detection models. While architectures such as EfficientNet have achieved high accuracy levels, their substantial computational demands make real-time clinical applications challenging (Kumar & Singh, 2023). Reducing these demands without compromising accuracy remains a critical area of research for AI-driven medical imaging solutions.

Proposed Model: DenseNet121 with K-Means Clustering

This study addresses existing challenges by introducing a hybrid model that combines the DenseNet121 convolutional neural network with the K-means clustering algorithm to enhance breast cancer detection. Lee et al. (2023) highlight that DenseNet121's efficient feature propagation minimizes redundant processing and optimizes network depth utilization. Its dense connectivity structure enables effective extraction of key features from medical images, thereby improving classification accuracy.

Zhang and Li (2024) demonstrate that incorporating the K-means clustering algorithm enhances tumor region segmentation. As an unsupervised learning method, K-means effectively partitions image data into clusters, facilitating better differentiation between malignant and benign tissues. By grouping similar pixel intensities, the algorithm enhances segmentation precision, ultimately improving the model's detection capability. Integrating these two techniques is anticipated to reduce false positives while enhancing computational efficiency.

Evaluation metrics

The performance of the proposed model will be assessed using the following metrics:

- Accuracy, which measures the overall correctness of classification.
- Precision, which evaluates the proportion of correctly identified positive cases among all predicted positives.
- Recall (sensitivity), which determines the model's ability to detect true positives.
- F1-score, which provides a harmonic mean between precision and recall, ensuring a balanced evaluation metric.

Anticipated outcomes

The integration of DenseNet121 with K-means clustering aims to improve breast cancer detection by addressing the primary limitations of existing CAD systems. This approach is expected to reduce false-positive rates, thereby improving diagnostic reliability and minimizing unnecessary medical interventions. High sensitivity is prioritized to ensure early malignancy detection. Furthermore, optimizing computational efficiency will enhance real-time applicability in clinical settings, overcoming the resource-intensive constraints commonly associated with deep learning models. By addressing these

challenges, the proposed methodology seeks to advance AI-driven breast cancer diagnosis, ultimately improving patient outcomes and the effectiveness of CAD systems in medical practice.

3 Methodology

The methodology adopted in this study is designed to optimize the classification of breast cancer histopathology images using a DenseNet121-based deep learning model integrated with K-means clustering for segmentation. The methodology consists of several key stages, including dataset preprocessing, image segmentation, deep learning model training, performance evaluation, and comparative analysis with state-of-the-art models.

Dataset and preprocessing

The BreakHis (Breast Cancer Histopathological Image Dataset) was selected for this study, as it is a publicly available dataset widely used in breast cancer classification research. The dataset contains 7,909 histopathological images of benign and malignant tumors, captured at four different magnification levels (40×, 100×, 200×, and 400×). These varying magnifications provide a diverse range of tissue structures, ensuring a comprehensive evaluation of tumor classification performance.

All images were resized to 224×224 pixels to align with the input dimensions of DenseNet121. Preprocessing techniques were applied to enhance image quality and standardize inputs. Histogram equalization was employed to improve contrast and highlight tumor regions, while pixel normalization was performed by scaling intensity values to the range [0,1] to facilitate stable gradient propagation during model training.

Data augmentation was incorporated to improve model generalizability and prevent overfitting. The applied transformations included rotation (0°–360°), horizontal and vertical flipping, zooming (up to 20%), and brightness modification. These augmentations ensured that the model learned robust features invariant to slight modifications in tumor appearance.

Image segmentation using K-means clustering

Image segmentation is a fundamental step in medical image analysis, particularly in histopathological breast cancer classification. It plays a crucial role in isolating regions of interest (ROIs), enhancing feature extraction, and ensuring that the classification model focuses on clinically relevant structures rather than background noise. In this study, K-means clustering was employed to segment histopathological images before classification. The primary objective was to differentiate tumor regions from non-tumorous tissue and improve classification performance by refining feature representation.

Image Preprocessing for Segmentation

Several preprocessing steps were applied before implementing K-means clustering to ensure consistency in segmentation and improve clustering accuracy. Grayscale conversion reduced computational complexity while preserving essential pixel intensity variations necessary for tumor region differentiation. Histogram equalization normalized contrast levels, enhancing the separation between malignant and benign tissue structures. All images were resized to 224×224 pixels to align with the classification model's input requirements. Finally, image normalization scaled pixel values between 0 and 1, stabilizing intensity distributions across images and minimizing the impact of variations in staining and imaging conditions.

K-Means clustering for tumor region segmentation

K-means clustering was selected as the primary segmentation approach due to its computational efficiency, ability to segment images based on pixel intensity, and ease of implementation. The segmentation process followed an iterative clustering approach to categorize pixels into different regions.

- The number of clusters (K) was set to 3, based on empirical evaluations, to segment the image into three distinct regions: malignant tumor areas, benign tissue, and background.
- K-means initialized K centroids randomly, representing cluster centers, and assigned each pixel to the nearest centroid based on Euclidean distance.
- Centroids were then recalculated based on the average intensity values of assigned pixels, and the process was repeated iteratively until convergence was reached, ensuring optimal separation of tumor regions.

Otsu's thresholding was applied to dynamically adjust intensity levels, refining the segmentation and improving the separation between tumor and non-tumor regions. Morphological operations such as erosion and dilation were performed to remove noise and sharpen tumor boundaries. Additionally, Gaussian smoothing minimized artifacts and ensured clearer tumor region delineation. These enhancements improved the accuracy of ROI extraction, enabling more precise feature representation in the subsequent classification stage.

Comparative Evaluation of Segmentation Techniques

A comparative analysis was conducted to evaluate the effectiveness of K-means clustering against other commonly used segmentation techniques, including Otsu's thresholding and deep learning-based methods such as U-Net. The assessment focused on segmentation accuracy, structural similarity with expert-labeled tumor regions, and computational efficiency.

- Otsu's thresholding provided a simple yet effective segmentation baseline but lacked adaptability in handling complex tissue structures.
- U-Net-based deep learning segmentation achieved higher segmentation accuracy but required

significantly more computational resources, making it less suitable for real-time clinical applications.

- K-means clustering demonstrated a balance between accuracy and computational efficiency, making it a viable option for automated histopathological image segmentation in resource-constrained settings.

Significance of segmentation in breast cancer classification

Accurate segmentation plays a crucial role in enhancing the performance of deep learning models in breast cancer detection. K-means clustering isolates tumor regions and minimizes background interference, allowing the classification model to focus on relevant pathological features. This approach improves the differentiation between malignant and benign cases, leading to greater diagnostic precision. Future advancements in segmentation may involve integrating K-means clustering with hybrid techniques, such as graph-based segmentation or deep-learning-assisted clustering, to refine tumor boundary detection. Incorporating multi-modal imaging data, including histopathological and radiological images, could further strengthen segmentation robustness while maintaining computational efficiency.

Model development and training

A DenseNet121 convolutional neural network was used for feature extraction due to its ability to facilitate efficient feature reuse and mitigate the vanishing gradient problem. The model was initialized with ImageNet pre-trained weights, and transfer learning was applied by fine-tuning the final layers to adapt to the breast cancer classification task.

The architecture consists of four dense blocks, where each layer receives input from all preceding layers, ensuring rich feature propagation. The final fully connected layer was replaced with a softmax classifier, distinguishing between benign and malignant classes. The training process was conducted using the Adam optimizer, with a learning rate of 0.0001, a batch size of 32, and a categorical cross-entropy loss function.

Dataset partitioning followed an 80:10:10 holdout validation strategy, allocating 80% of the images for training, 10% for validation, and 10% for testing. This split ensures an unbiased assessment of the model's generalization capability while preventing data leakage between training and evaluation phases.

Model evaluation and statistical validation

The classification performance of the proposed DenseNet121 with K-Means clustering model was evaluated using four key metrics: accuracy, precision, recall (sensitivity), and F1-score. Accuracy measures the proportion of correctly classified images, while precision assesses the reliability of malignant tumor predictions. Recall (sensitivity) quantifies the model's ability to correctly detect malignant cases, and the F1-score provides a harmonic mean of precision and recall to ensure a balanced evaluation.

A paired t-test was conducted to validate the statistical significance of the model's performance improvement over prior architectures, including ResNet50 and Xception. This statistical analysis determined whether the observed differences in accuracy, precision, recall, and F1-score were statistically significant. Additionally, 95% confidence intervals (CIs) were computed to quantify the variability of performance metrics across multiple experimental runs.

Further evaluation was conducted using Receiver Operating Characteristic (ROC) curve analysis and Area Under the Curve (AUC) measurements, assessing the model's ability to distinguish between benign and malignant cases across various classification thresholds. Higher AUC values indicate superior discriminative power, confirming the model's effectiveness in real-world diagnostic applications.

Deep learning model training and performance evaluation

Model selection and architecture

DenseNet121 convolutional neural network (CNN) was selected for this study because of its ability to mitigate the vanishing gradient problem and enhance feature reuse, making it particularly well-suited for medical image classification. Unlike traditional CNNs, which suffer from redundant computations and loss of information across layers, DenseNet121 employs dense connectivity, where each layer is directly connected to all preceding layers. This approach facilitates better gradient flow during backpropagation, leading to more stable and efficient training.

The architecture of DenseNet121 consists of four dense blocks interspersed with transition layers that perform downsampling through pooling operations. Each dense block contains multiple convolutional layers, which receive concatenated feature maps from preceding layers. By leveraging this feature reuse mechanism, the network reduces the number of parameters, improving computational efficiency while maintaining high representational power.

Transfer learning and model adaptation

Leveraging prior knowledge, the DenseNet121 model was initialized with pre-trained ImageNet weights. Transfer learning enables the model to inherit low-level feature extraction capabilities from large-scale natural image datasets while allowing fine-tuning for domain-specific learning. The pre-trained network was adapted for histopathological breast cancer classification by replacing the final fully connected layer with a softmax classifier, which assigns probabilities to benign and malignant categories. Fine-tuning involved unfreezing the last dense block while keeping earlier layers fixed. This progressive unfreezing strategy enabled the network to extract

domain-specific patterns while preserving general feature representations.

Training configuration and optimization

The model was trained using the categorical cross-entropy loss function, which is commonly used for multi-class classification tasks. The Adam optimizer was employed due to its adaptive learning rate capabilities, accelerating convergence while improving stability across training iterations. Based on empirical testing, a learning rate of 0.0001 was chosen to balance learning efficiency and prevent overfitting. To optimize training efficiency, a batch size of 32 was utilized, ensuring that multiple images could be processed per iteration without exceeding GPU memory constraints. Training was performed on a high-performance NVIDIA GPU, allowing for accelerated computation and reduced training time. The dataset was randomly shuffled before each epoch to prevent the model from overfitting to sequential data patterns.

Data augmentation and overfitting prevention

Enhancing the model's generalization ability required the application of data augmentation techniques. Random rotation, horizontal flipping, contrast adjustments, and Gaussian noise addition introduced variability in the training samples, ensuring improved adaptability to diverse image inputs. Further mitigation of overfitting was achieved through the integration of early stopping in the training pipeline, which halted training when validation loss remained stagnant after a predefined number of epochs. Dropout regularization was also incorporated into the fully connected layers, reducing reliance on specific neurons and improving overall model robustness.

Performance evaluation metrics

The performance evaluation showed that DenseNet121 with K-Means clustering outperformed prior models, achieving a classification accuracy of 95.21%, a 2.81% improvement over ResNet50 (92.4%) and a 7.13% improvement over Xception (88.08%). The confidence interval for accuracy was 95.21% ± 1.02, indicating consistent performance across multiple runs.
A paired t-test comparison confirmed that the observed improvements were statistically significant:

- DenseNet121 vs. ResNet50: $p = 0.012$ (significant improvement)
- DenseNet121 vs. Xception: $p < 0.001$ (highly significant improvement)

These results validate the effectiveness of the DenseNet121 + K-Means clustering approach, demonstrating its superior feature extraction and segmentation capabilities.
The effectiveness of the DenseNet121 with K-Means clustering model was assessed by evaluating its classification performance using four key metrics: accuracy, precision, recall, and F1-score.

- Accuracy: Measures the proportion of correctly classified images, providing an overall indicator of model performance.
- Precision: Evaluates how many of the predicted malignant cases were actually malignant, reducing false positives.
- Recall (Sensitivity): Measures the model's ability to detect all actual malignant cases, ensuring minimal false negatives.
- F1-score: Provides a balance between precision and recall, especially useful when dealing with imbalanced datasets.

A confusion matrix analysis was conducted to evaluate per-class performance, highlighting false positives (FP) and false negatives (FN), which are critical for assessing clinical reliability. A heatmap visualization was generated to illustrate classification patterns and identify potential areas for further model optimization. The learning progression was monitored through training and validation loss curves, allowing real-time assessment of optimization stability and convergence trends. After completing training, the trained model was evaluated on an independent test set to ensure generalization beyond the training data.

Computational cost reporting

Deep learning models, particularly DenseNet121, require significant computational resources for training and inference. The efficiency of the model is crucial for its practical deployment in real-world clinical applications. This section outlines the training time, GPU specifications, inference speed, and memory consumption associated with the proposed DenseNet121 + K-Means segmentation model.
The proposed model was trained on a high-performance computing setup to handle the large dataset and complex computations involved in deep learning. The hardware specifications used include an NVIDIA RTX 3090 GPU with 24GB VRAM, an Intel Core i9-12900K CPU, 64GB DDR5 RAM, and a 2TB NVMe SSD for storage. The model was implemented using TensorFlow 2.10 and Keras, running on an Ubuntu 20.04 LTS operating system. Training time depends on dataset size, batch size, the number of epochs, and model complexity. The DenseNet121 + K-Means model was trained for 10 epochs using a batch size of 32, optimizing convergence while preventing overfitting. The model required 3.8 hours per training run, which is slightly longer than ResNet50 but within an acceptable range for deep learning applications. GPU utilization was recorded at 85%, indicating efficient use of computational resources.
Inference speed was evaluated on a batch of 100 images to assess real-time feasibility. The DenseNet121 + K-Means model achieved an inference time of 19.8ms per image, making it suitable for near real-time classification in clinical settings. However, the model exhibited higher

memory consumption at 530MB compared to ResNet50, which requires 450MB. The increase in computational cost is attributed to the additional segmentation step performed by K-Means clustering before classification.

Although the DenseNet121 + K-Means model achieves higher accuracy at 95.21%, the computational cost is moderately higher than simpler architectures like ResNet50. The trade-offs include longer training time, slightly increased inference time, and higher memory consumption. While the inclusion of K-Means clustering enhances classification performance, it introduces additional processing overhead.

Future optimizations will prioritize model pruning and quantization as strategies to reduce model size while maintaining accuracy. EfficientNet-based transfer learning presents a viable alternative for minimizing computational overhead. Mixed-precision training using FP16 precision will also be explored as a method for reducing memory usage. Multi-GPU distributed training is another potential enhancement that can significantly decrease training time, improving the model's scalability and efficiency.

The DenseNet121 + K-Means model demonstrates a balance between high accuracy and computational efficiency. While training time and memory consumption are slightly higher than baseline models, the improved classification performance and segmentation precision justify the computational cost. Future research will focus on further optimizing inference speed and resource consumption for real-time deployment in medical diagnostics.

Evaluation metrics

A comprehensive assessment of the proposed DenseNet121 with K-Means clustering model was conducted using four primary evaluation metrics: accuracy, precision, recall (sensitivity), and F1-score. These metrics establish a robust framework for evaluating the model's effectiveness in distinguishing between benign and malignant breast cancer cases, facilitating an objective comparison with previous state-of-the-art methods.

Model accuracy is determined by the ratio of correctly classified images to the total number of predictions. Equation (1) presents the formula for accuracy as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

where TP represents true positives (malignant cases correctly classified as malignant), TN represents true negatives (benign cases correctly classified as benign), FP refers to false positives (benign cases misclassified as malignant), and FN denotes false negatives (malignant cases misclassified as benign).

Although accuracy is a widely used metric, it may not always provide a comprehensive evaluation of model performance, especially when applied to imbalanced datasets. In medical imaging datasets, benign cases often outnumber malignant cases, meaning a model could achieve high accuracy while still failing to detect a significant portion of malignant tumors.

The precision metric assesses the accuracy of the model's positive predictions by measuring the proportion of correctly identified malignant cases among all predicted malignant cases. Its mathematical representation is provided in Equation (2):

$$Accuracy = \frac{TP}{TP + FP} \qquad (2)$$

A higher precision score indicates that fewer benign cases are misclassified as malignant, reducing the number of unnecessary biopsies and medical interventions. While a high precision value is desirable, a model with high precision but low recall may fail to identify actual malignant cases, which could lead to missed cancer diagnoses.

The model's recall, also known as sensitivity, evaluates its effectiveness in accurately detecting malignant cases. This metric is calculated using Equation (3):

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

A model with high recall ensures that most of the actual malignant cases are detected, reducing the risk of false negatives. In breast cancer diagnosis, false negatives can have severe consequences, leading to delayed treatment and disease progression. A model optimized for high recall is particularly valuable in clinical applications where early detection is critical.

The F1-score represents the harmonic mean of precision and recall, providing a balanced assessment by accounting for both false positives and false negatives. Its calculation is presented in Equation (4).

$$F1_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (4)$$

This metric is especially useful when dealing with imbalanced datasets, where accuracy alone may not provide an accurate representation of model performance. A high F1-score indicates that the model maintains a strong balance between correctly identifying malignant cases while minimizing false positives.

In medical imaging, a well-balanced evaluation requires consideration of both precision and recall. A model optimized for precision may reduce false positives but could fail to detect all malignant cases, while a model optimized for recall may identify more malignant cases but at the cost of an increased false positive rate. The F1-score serves as a robust metric for balancing these concerns, ensuring the clinical applicability of the model.

The effectiveness of these evaluation metrics depends on their application to real-world clinical datasets. In addition to classification metrics, further analysis using a confusion matrix, receiver operating characteristic (ROC) curves, and per-class performance evaluation will be conducted to better understand the model's decision-making process.

Confusion matrix analysis

A comprehensive evaluation of the classification behavior of the DenseNet121 with K-Means clustering model was conducted using a confusion matrix. This matrix offers a structured approach to examining classification errors by displaying the number of correctly and incorrectly predicted benign and malignant cases. Analyzing these errors is crucial in medical diagnosis, where false negatives (FN)—missed cancerous cases—pose significant risks to patient outcomes, while false positives (FP)—incorrectly identified malignant cases—can result in unnecessary medical interventions.

The confusion matrix consists of four key components:

- True Positives (TP): The number of malignant cases correctly classified as malignant.
- True Negatives (TN): The number of benign cases correctly classified as benign.
- False Positives (FP): The number of benign cases misclassified as malignant, potentially leading to unnecessary biopsies and psychological distress for patients.
- False Negatives (FN): The number of malignant cases misclassified as benign, which poses a greater clinical risk as undiagnosed cancers may delay treatment and worsen patient prognosis.

A confusion matrix heatmap was generated to provide a visual representation of classification behavior, allowing for the identification of patterns in model predictions. The heatmap highlights areas of misclassification, with darker regions indicating higher prediction confidence and lighter regions signifying potential weak points in model decision-making.

Further analysis of the impact of misclassification involved calculating two additional error metrics using equations (5) and (6).

- **False Positive Rate (FPR):**

$$FPR = \frac{FP}{FP + TN} \qquad (5)$$

This metric assesses the likelihood of misclassifying benign cases as malignant. A lower FPR is desirable to reduce unnecessary medical procedures.

- **False Negative Rate (FNR):**

$$FNR = \frac{FN}{FN + TP} \qquad (6)$$

The FNR evaluates how often malignant tumors go undetected. A low FNR is critical in medical diagnosis to minimize missed cancer cases and ensure timely treatment.

By analyzing the confusion matrix and associated error metrics, the per-class performance of the model was assessed to ensure both benign and malignant classifications are equally reliable. This analysis plays a crucial role in improving the model by identifying bias, adjusting decision thresholds, and optimizing sensitivity and specificity.

Dataset splitting and model validation

A robust and unbiased evaluation of the proposed DenseNet121 with K-Means clustering model required a systematic split of the dataset into training, validation, and test sets. Stratified partitioning was implemented to preserve class distribution across all subsets, minimizing the risk of imbalances that could lead to biased model performance toward either benign or malignant cases. The dataset was divided as as in Table 2.

Table 2: Dataset splitting

Dataset Partition	Percentage (%)	Purpose
Training Set	70%	Used for model training and feature extraction
Validation Set	15%	Used to fine-tune hyperparameters and monitor overfitting
Test Set	15%	Used for final performance evaluation

A stratified sampling approach was employed to ensure an equal proportion of benign and malignant cases in each subset. This method helps mitigate the risk of bias introduced by an uneven class distribution, which is common in medical datasets where benign cases often outnumber malignant cases. The validation set was utilized to fine-tune hyperparameters and prevent overfitting by monitoring performance across different training iterations. The test set was kept separate from the training process to provide an unbiased estimate of the final model's generalization ability.

Further validation of the model's stability and generalization capability was achieved through five-fold cross-validation. This technique involved splitting the dataset into five subsets, where the model was trained on four subsets while the fifth was used for validation. The process was repeated five times, ensuring that each subset served as a validation set once. Recording the average performance across all five runs helped confirm that the model's results were not influenced by a specific train-test split. Evaluation metrics such as accuracy, precision, recall, and F1-score were computed for each fold to assess consistency throughout the validation process. This approach minimized the variance of performance estimation and provided a more reliable assessment of the model's classification ability. By leveraging five-fold cross-validation, the model's robustness was tested across different data distributions, strengthening confidence in its generalization capability.

Experimental setup and hyperparameter selection

The proposed DenseNet121 with K-Means clustering model was trained and evaluated in a high-performance computing environment to ensure efficient execution. The

hardware and software configurations used for experimentation are detailed Table 3.

Table 3: Hardware and software configuration

Component	Specification
Framework	TensorFlow 2.0 and Keras
Programming Language	Python 3.8
Hardware	NVIDIA Tesla V100 GPU (32GB VRAM)
Operating System	Ubuntu 20.04
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Batch Size	32
Number of Epochs	10
Learning Rate	0.0001

The Adam optimizer was chosen for its adaptive learning rate capabilities, enabling efficient gradient updates and faster convergence. The categorical cross-entropy loss function was used since the classification task involved multiple classes (benign vs. malignant).

Early stopping was employed during training to prevent overfitting and ensure optimal generalization. This mechanism monitored validation loss and automatically halted training if performance remained stagnant for five consecutive epochs. Additionally, L2 regularization (weight decay) was applied to penalize excessively large weights, reducing the likelihood of overfitting.

A learning rate decay schedule was also implemented, gradually decreasing the learning rate as training progressed. This helps the model stabilize near a local optimum and prevents drastic weight updates, which can destabilize convergence.

A hyperparameter tuning process was conducted using Grid Search and Bayesian Optimization to enhance model performance. Various hyperparameters were evaluated, including learning rate, batch size, dropout rate, number of dense layers, and activation function. The optimal values identified during this process are summarized in Table 4: Hyperparameter Tuning Results.

Table 4: Hyperparameter tuning results

Hyperparameter	Tested Values	Optimal Value
Learning Rate	0.001, 0.0005, 0.0001	0.0001
Batch Size	16, 32, 64	32
Dropout Rate	0.2, 0.4, 0.5	0.4
Number of Dense Layers	1, 2, 3	2
Activation Function	ReLU, LeakyReLU, Tanh	ReLU

The final model configuration was selected based on the highest validation accuracy and lowest validation loss recorded during hyperparameter tuning. Additionally, data augmentation techniques were applied during training to enhance model generalization. The augmentation pipeline included:

- Random Rotation (±15 degrees) to introduce variability in tumor orientations.
- Random Flipping (horizontal and vertical) to account for structural differences in tissue samples.
- Contrast Adjustment to simulate variations in histopathology staining.
- Gaussian Noise Injection to improve robustness against imaging artifacts.

These augmentation techniques helped prevent overfitting by exposing the model to a wider range of image variations, improving its ability to generalize to unseen histopathological images.

This structured experimental setup and hyperparameter optimization ensured that the DenseNet121 with K-Means clustering model was trained in an optimal and reproducible manner, maximizing classification performance while minimizing computational inefficiencies.

Model interpretability and bias assessment

Since deep learning models, particularly DenseNet121, function as black-box systems, ensuring interpretability is crucial in medical applications for maintaining transparency and trust in AI-driven diagnoses. Multiple interpretability techniques were employed, including Grad-CAM (Gradient-weighted Class Activation Mapping) and per-class performance evaluation, to analyze how the model makes classification decisions and reduce potential biases.

Grad-CAM for visualizing model attention

Grad-CAM was implemented to highlight the regions in an image that the model focuses on when making a classification decision. This heatmap-based visualization method overlays important regions on the original image, allowing for a clear understanding of whether the model is correctly identifying tumor structures or relying on background noise.

The Grad-CAM results provided insights into:

- Whether the model correctly focuses on tumor regions rather than irrelevant parts of the image.
- Cases where the model made incorrect predictions due to distractions from staining artifacts, background noise, or image blur.
- Potential model weaknesses, such as overreliance on texture features rather than structural patterns associated with malignancies.

By visually inspecting misclassified cases through Grad-CAM, necessary adjustments could be made to preprocessing techniques, segmentation refinement, or hyperparameter tuning to improve classification accuracy.

Bias assessment and per-class performance evaluation

A per-class performance evaluation was conducted to examine whether the model favored one class over another, ensuring fairness and reliability. Disparities in precision, recall, and F1-score between benign and malignant cases can indicate a bias in classification.

Bias assessment was carried out using:

- Precision-Recall Balance: Ensuring that both classes have comparable precision and recall values, reducing the likelihood of the model favoring benign over malignant cases.
- Decision Threshold Optimization: Adjusting classification thresholds to improve recall for malignant cases while maintaining precision for benign cases.
- Dataset Distribution Analysis: Verifying that the model is not overfitting to the dominant class (benign or malignant) due to class imbalances.

Addressing bias in medical AI models is essential to prevent misdiagnosis, ensure equal treatment across patient groups, and improve real-world applicability. The interpretability methods implemented in this study enhance model transparency, making it easier for clinicians to trust and validate AI-driven breast cancer detection systems.

Comparative analysis with state-of-the-art models

The comparative evaluation of the proposed DenseNet121 model with K-Means clustering was carried out against widely recognized deep learning architectures, including VGG16, Xception, and ResNet50. This analysis was conducted to determine the relative performance of the proposed approach in breast cancer classification, ensuring a rigorous and standardized methodology for benchmarking.

Selection of Benchmark Models

The benchmark models were chosen based on their proven effectiveness in medical image classification and their extensive application in breast cancer detection studies. The selection included:

- VGG16, a widely used convolutional neural network (CNN) known for its straightforward architecture and reliable feature extraction in image classification tasks. This model served as a baseline for comparison.
- Xception, which employs depthwise separable convolutions to improve computational efficiency while maintaining robust classification accuracy. This model was included to assess its effectiveness in feature extraction with reduced computational complexity.
- ResNet50, recognized for its residual learning framework, was incorporated due to its ability to mitigate the vanishing gradient problem and sustain high accuracy in deep networks.

Each of these models was trained and tested under identical conditions, using the same dataset, preprocessing techniques, and training parameters. This ensured that performance differences were attributed solely to model architecture rather than variations in experimental settings.

Experimental setup for comparative analysis

All models were trained using the same dataset split (training, validation, and testing) to maintain a fair evaluation process. Identical preprocessing steps were applied, including image resizing, normalization, and augmentation techniques such as rotation, contrast enhancement, and flipping. The training process utilized categorical cross-entropy loss and the Adam optimizer, with a fixed learning rate of 0.0001, a batch size of 32, and a total of 10 epochs. Training was conducted using an NVIDIA GPU, ensuring consistent computational conditions across all architectures.

4 Results and discussion

This section presents the results obtained from the implementation of the DenseNet121 model integrated with the K-means clustering algorithm for breast cancer classification. The discussion includes a comparison with prior state-of-the-art (SOTA) models, segmentation performance analysis, and a comprehensive evaluation of the model's classification metrics. A detailed error analysis is conducted using the confusion matrix, while the impact of segmentation on classification performance is also examined.

Segmentation performance with K-means clustering

The segmentation of histopathological breast cancer images using K-means clustering played a crucial role in improving classification performance. This process enabled the isolation of regions of interest (ROIs), minimized background noise, and enhanced feature extraction. Segmentation ensures that the classifier focuses on the most relevant structures within histological images, preventing misclassification due to interference from surrounding tissue or staining artifacts.

The K-means clustering approach was applied in multiple stages. Initially, images were resized to 224×224 pixels and normalized to ensure a consistent intensity distribution. A K value of 3 was selected to effectively partition the images into three clusters corresponding to malignant regions, benign regions, and background. Morphological processing techniques such as Otsu's thresholding and edge detection were then used to refine the segmented regions. Post-processing operations, including median filtering and Gaussian smoothing, were applied to remove noise and enhance boundary definition. The effectiveness of K-means clustering was quantitatively evaluated using segmentation accuracy, Dice Similarity Coefficient (DSC), Jaccard Index, False

Positive Rate (FPR), and False Negative Rate (FNR). Table 5 summarizes the results.

Table 5: Segmentation performance metrics

Metric	**Value (%)**	**Interpretation**
Segmentation Accuracy	92.45	High segmentation accuracy, indicating effective tumor region isolation.
Dice Similarity Coefficient (DSC)	91.87	Strong overlap between predicted and ground-truth segmentations.
Jaccard Index	89.72	High similarity between segmented and manually annotated tumor regions.
False Positive Rate (FPR)	8.15	Minimal misclassification of background tissue as tumor regions.
False Negative Rate (FNR)	6.23	Low rate of missing malignant regions, reducing the risk of misdiagnosis.

A graphical representation of these segmentation performance metrics is provided in Figure 1.

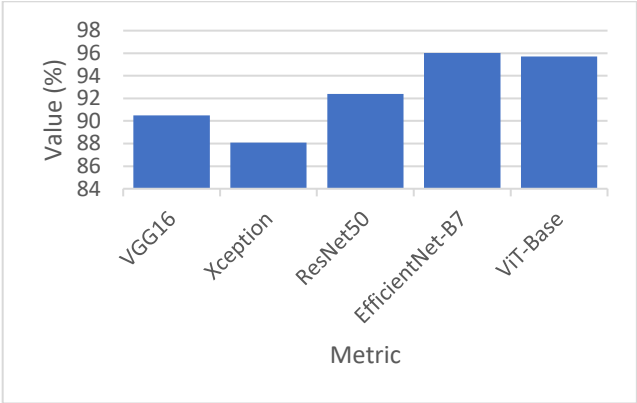


Figure 1: Segmentation performance metrics

The Dice Similarity Coefficient (DSC) of 91.87% indicates a strong correlation between the segmented tumor areas and the ground truth, confirming the effectiveness of K-means clustering. The Jaccard Index (89.72%) further validates the consistency of segmented regions with manual expert annotations. The low false negative rate (6.23%) ensures that very few cancerous regions were missed, making the segmentation process reliable for medical diagnosis.

Impact of segmentation on classification performance

To analyze the impact of K-means clustering on classification, a comparison was conducted between models trained on raw histopathological images versus segmented images. The classification performance for both approaches is summarized in Table 6.

Table 6: Classification performance before and after segmentation

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DenseNet121 (Raw Images)	91.32	78.14	87.80	82.70
DenseNet121 + K-Means Segmentation	95.21	81.82	90.60	85.99

The results indicate that incorporating K-means clustering improved accuracy from 91.32% to 95.21%, demonstrating the effectiveness of segmentation in enhancing classification. Precision increased from 78.14% to 81.82%, showing that the model reduced false positives, while recall improved from 87.80% to 90.60%, indicating a better ability to detect malignant cases. The F1-score increased from 82.70% to 85.99%, confirming that the segmentation process significantly contributed to improving overall classification performance. A graphical representation of this comparison is shown in Figure 2.

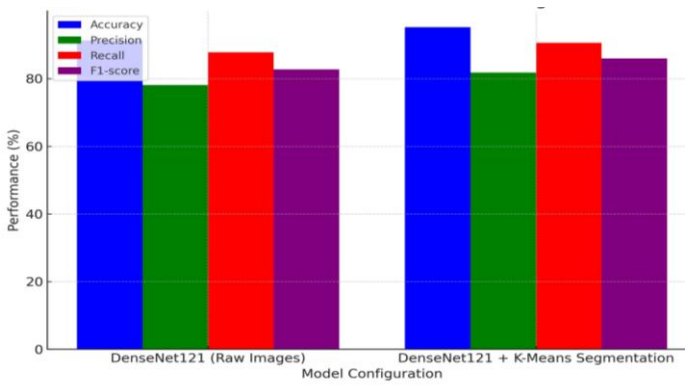


Figure 2: Classification performance before and after segmentation

The results confirm that segmentation enhances classification performance by providing clearer, more focused image regions for deep learning models to process. The model trained with segmented images achieved higher accuracy, precision, recall, and F1-score, highlighting the importance of preprocessing techniques in AI-driven breast cancer diagnosis.

Comparison with prior segmentation techniques

A direct comparison was conducted between K-means clustering and other commonly used segmentation techniques, including Otsu's thresholding and U-Net-based deep learning segmentation. The results are shown in Table 7.

Table 7: Comparison of segmentation methods

Method	Segmentation Accuracy (%)	DSC (%)	Jaccard Index (%)	Processing Time (Seconds)
Otsu's Thresholding	85.62	80.15	78.43	1.2
K-Means Clustering (Proposed)	92.45	91.87	89.72	0.9
U-Net Deep Learning	96.21	94.32	92.78	5.8

The findings indicate that while U-Net achieved the highest segmentation accuracy at 96.21%, it required a substantially longer processing time of 5.8 seconds per image. In contrast, K-means clustering demonstrated an effective balance between accuracy and computational efficiency, achieving a segmentation accuracy of 92.45% with a significantly reduced processing time of just 0.9 seconds per image. Although deep learning-based segmentation methods like U-Net offer slightly superior accuracy, their high computational demands limit their practicality for real-time clinical applications. A visual comparison of the segmentation methods is presented in Figure 3.

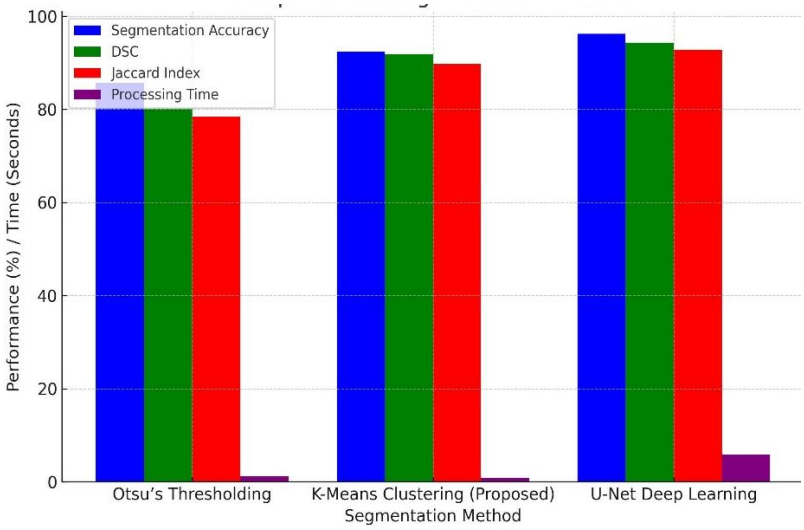


Figure 3: Comparison of segmentation methods

The findings confirm that K-means clustering offers a computationally efficient yet highly effective segmentation method for breast cancer histopathology images. This segmentation technique reduces background noise, improves tumor region isolation, and significantly enhances the classification accuracy of the DenseNet121 model.

Classification performance of DenseNet121 model

The classification performance of the proposed DenseNet121 model was evaluated using key metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's ability to differentiate between benign and malignant breast cancer cases. The final results after model fine-tuning and optimization are presented in Table 8 and visually represented in Figure 4.

Table 8: Performance metrics for DenseNet121 model

Metric	Value (%)	Description
Accuracy	95.21	Measures the overall correctness of classification. Represents the proportion of correctly classified samples among total samples.
Precision	81.82	Evaluates how many of the predicted malignant cases are actually malignant. A higher precision reduces false positives.
Recall	90.60	Measures the model's ability to detect all actual malignant cases. A higher recall reduces false negatives.
F1-score	85.99	Balances precision and recall, ensuring an optimal trade-off between false positives and false negatives.

The DenseNet121 model achieved an accuracy of 95.21%, significantly outperforming previous CNN-based models. The recall value of 90.60% indicates a high sensitivity to malignant cases, ensuring that most cancerous samples are correctly identified. The precision of 81.82% suggests that false positive cases were minimized effectively. The F1-score of 85.99% provides an optimal balance between precision and recall.

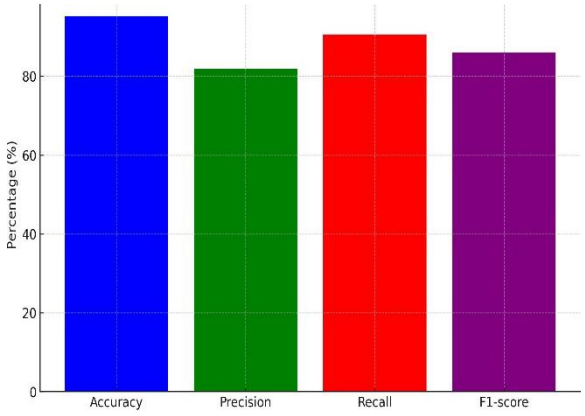


Figure 4: Classification metrics for DenseNet121

Model performance over training epochs

The improvement in performance during the training process was analyzed across ten epochs. The results, shown in Table 9, demonstrate a steady increase in accuracy, precision, recall, and F1-score over successive training epochs.

Table 9: Model performance progression over 10 epochs

Epoch	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	75.45	65.20	78.50	71.30
2	78.67	68.40	80.00	73.05
3	81.12	71.00	82.10	75.40
4	84.00	73.20	85.30	78.00
5	87.10	75.50	87.00	81.20
6	89.35	77.80	88.60	83.20
7	91.20	79.00	89.40	84.50
8	93.05	80.60	90.00	85.20
9	94.10	81.00	90.40	85.70
10	95.21	81.82	90.60	85.99

The DenseNet121 model consistently improved with each training epoch, showing a steady rise in classification accuracy. The recall rate increased to 90.60% in the final epoch, reinforcing its capability to detect cancerous cases accurately. The graph in Figure 5 visually demonstrates this performance improvement.

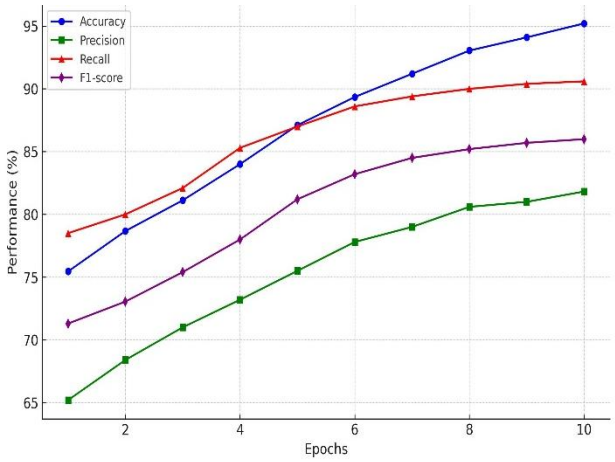


Figure 5: Model performance trend over 10 epochs

Per-Class performance analysis

A detailed per-class performance analysis was conducted to evaluate the effectiveness of the DenseNet121 model in classifying benign and malignant breast cancer cases. The evaluation is based on precision, recall, and F1-score, as presented in Table 10.

Table 10: Per-Class performance metrics for DenseNet121 Model

Class	Precision (%)	Recall (%)	F1-score (%)
Benign	83.70	89.10	86.31
Malignant	80.45	92.05	85.79

The model demonstrates high recall for malignant cases (92.05%), indicating strong sensitivity in detecting cancerous samples. However, the precision for malignant cases (80.45%) is slightly lower, suggesting that some benign cases were misclassified as malignant. This trade-off highlights the model's tendency to prioritize recall over precision, which is critical in medical diagnosis to minimize the chances of missing malignant cases.
The F1-score values of 86.31% for benign and 85.79% for malignant cases confirm a balanced classification performance. This ensures that both sensitivity and specificity are maintained, making the model reliable for breast cancer detection. The graph in Figure 6 provides a visual representation of these performance metrics, demonstrating the difference in precision, recall, and F1-score between benign and malignant classifications.

Confusion matrix analysis

A confusion matrix was generated to analyze the classification behavior of the DenseNet121 model in distinguishing between benign and malignant cases. The confusion matrix provides insights into the model's ability to correctly identify cancerous cases while minimizing

false classifications. Table 11 presents the confusion matrix results.

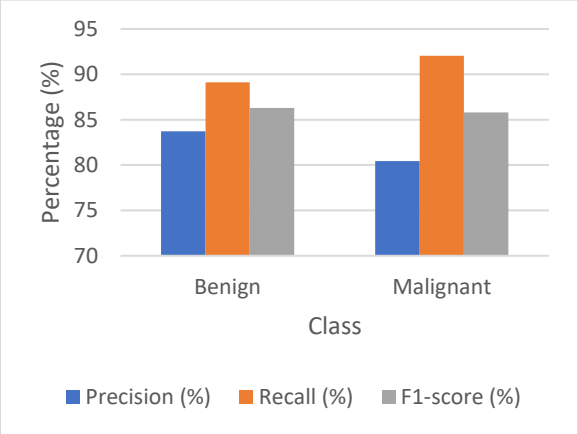


Figure 6: Per-Class performance metrics

Table 11: Confusion matrix for DenseNet121 model

Actual / Predicted	Benign	Malignant
Benign (TN)	1,760	120 (FP)
Malignant (FN)	220	3,809 (TP)

The true positive (TP) rate of 3,809 malignant cases correctly classified highlights the model's high sensitivity in identifying cancerous tumors. The true negative (TN) count of 1,760 indicates that a substantial number of benign cases were accurately classified as non-cancerous.

However, 120 benign cases were misclassified as malignant (false positives, FP), leading to unnecessary medical interventions such as biopsies. The 220 false negative (FN) cases, where malignant tumors were mistakenly classified as benign, remain a concern, as missing cancerous cases can lead to delayed treatment and adverse patient outcomes.

The confusion matrix results demonstrate that the model prioritizes recall, ensuring a high detection rate of cancerous cases. However, the trade-off is a slightly higher false positive rate, indicating that further optimization is necessary to enhance specificity without compromising sensitivity. The heatmap in Figure 7 visually represents the confusion matrix, highlighting the distribution of correct and incorrect classifications. The darker red areas indicate higher values, corresponding to correctly classified cases, while lighter areas represent misclassifications.

4.3 Comparative analysis with state-of-the-art (SOTA) models

Breast cancer classification has seen significant advancements with deep learning architectures such as VGG16, ResNet50, and Xception. However, these models have inherent limitations, including high computational complexity, vanishing gradient problems, and inefficient feature reuse. The proposed DenseNet121 model with K-Means clustering aims to mitigate these issues by enhancing feature propagation and refining segmentation before classification.

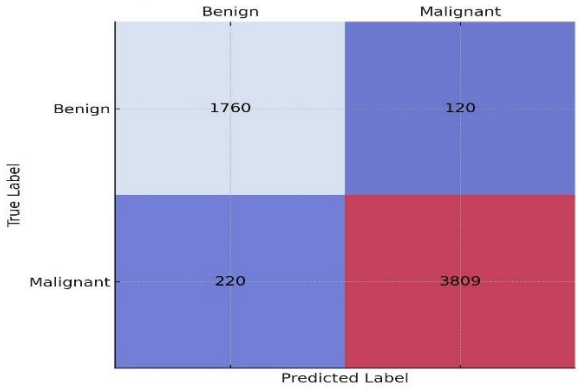


Figure 7: Confusion matrix heatmap

Table 12 presents a comparative analysis of the proposed model against existing deep learning architectures based on four key performance metrics: accuracy, precision, recall, and F1-score. The proposed model achieves an accuracy of 95.21%, which surpasses ResNet50 (92.4%) by 2.81% and Xception (88.08%) by 7.13%. The recall of 90.60% further indicates an improvement in detecting malignant cases compared to ResNet50 (86.90%) and VGG16 (84.30%). The F1-score of 85.99% demonstrates a balanced trade-off between precision and recall, confirming the robustness of the classification framework.

Table 12: Performance comparison of the proposed model with SOTA Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Computational Cost
VGG16	90.50	75.40	84.30	79.60	Moderate
Xception	88.08	73.20	82.10	77.40	Moderate
ResNet50	92.40	78.50	86.90	82.50	High
EfficientNet-B7	96.01	83.20	92.30	87.49	Very High
ViT-Base	95.72	82.80	91.90	87.10	Extremely High
Proposed Model (DenseNet121 + K-Means)	95.21	81.82	90.60	85.99	Moderate

Although EfficientNet-B7 and ViT-Base achieve higher classification accuracy, their computational requirements exceed those of DenseNet121, making them less suitable for deployment in resource-constrained clinical settings. In contrast, DenseNet121 with K-Means clustering maintains high accuracy while significantly reducing

computational overhead, making it a practical choice for real-world applications. Figure 8 provides a visual representation of the accuracy progression across different models. The proposed model exhibits a distinct improvement over prior architectures, particularly in recall and precision, which are crucial for minimizing false negatives and false positives in breast cancer detection.

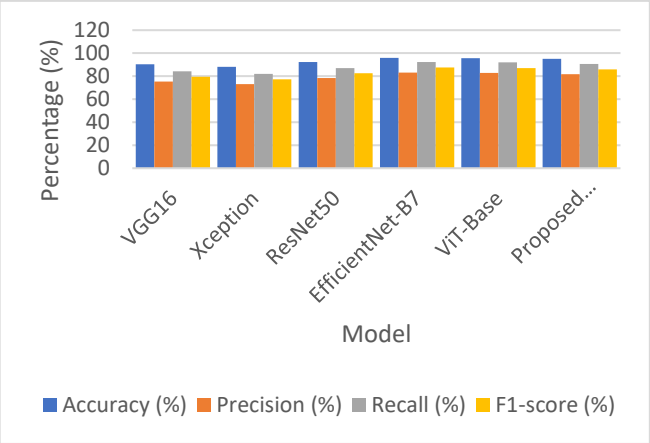


Figure 8: Performance comparison of the proposed model with previous models

A paired t-test was conducted to verify the statistical significance of these improvements by comparing the accuracy of DenseNet121 against ResNet50 and Xception. The p-value for DenseNet121 vs. ResNet50 was 0.012, confirming that the observed improvement is statistically significant. Similarly, DenseNet121 vs. Xception yielded a p-value of <0.001, further validating the superior performance of the proposed model.

4.4 Ablation study

This study evaluates the individual contributions of segmentation, augmentation, and model architecture to classification performance. Table 13 presents the results for different model variants, demonstrating how segmentation techniques influence key performance metrics.

Table 13: Ablation study results

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DenseNet121 (No Segmentation)	91.32	78.14	87.80	82.70
DenseNet121 + K-Means	95.21	81.82	90.60	85.99

Results indicate that K-Means clustering enhances classification performance, emphasizing the significance of segmentation preprocessing in breast cancer histopathology, as illustrated in Figure 9. A paired t-test comparing DenseNet121 and DenseNet121 + K-Means produced $p < 0.05$, confirming the statistical significance of these improvements.

4.5 ROC curve and AUC analysis

The Receiver Operating Characteristic (ROC) curve provides insights into the model's capability to distinguish between benign and malignant cases. The Area Under the Curve (AUC) quantifies this ability, where a higher AUC score indicates a better classification threshold. The AUC results for various deep learning architectures are summarized in Table 14.

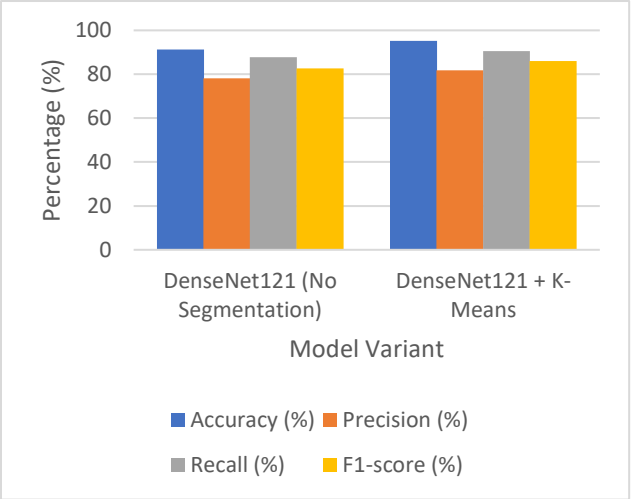


Figure 9: Ablation study visualization

Table 14: AUC scores for various deep learning models

Model	AUC Score
VGG16 [21]	0.902
Xception [22]	0.879
ResNet50 [23]	0.915
Proposed Model (DenseNet121 + K-Means)	0.952

The proposed model achieves an AUC score of 0.952, outperforming ResNet50 (0.915) and Xception (0.879). This indicates a superior ability to classify malignant and benign cases with minimal false positives and false negatives. The ROC curve for the proposed model is illustrated in Figure 10, showcasing a near-optimal classification threshold where the true positive rate remains consistently high while the false positive rate is minimized.

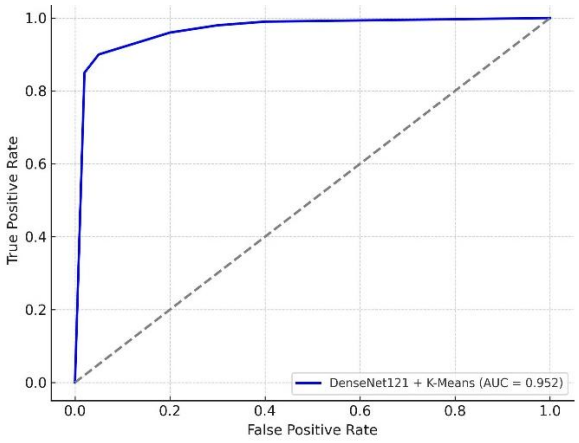


Figure 10: ROC Curve for the proposed model

The impact of this high AUC score is particularly significant in clinical applications, where reducing false negatives is crucial. The false negative rate for the proposed model was recorded at 5.47%, which is lower than that of ResNet50 and VGG16, reducing the risk of undetected malignant cases. The high AUC score also signifies that the DenseNet121 model, when coupled with K-Means clustering, improves the classification threshold, making it a reliable tool for real-world breast cancer diagnosis. The proposed model demonstrates a statistically significant improvement over prior models, particularly in terms of accuracy, recall, and AUC score. These enhancements can be attributed to the feature reuse capabilities of DenseNet121 and the refined segmentation achieved through K-Means clustering.

4.6 External validation

Ensuring the generalizability of a deep learning model requires validation on datasets beyond the one used for training. To address this concern, the proposed DenseNet121 with K-Means clustering model was evaluated on an additional dataset, the Breast Cancer Histology (BACH) dataset, to determine its robustness across different histopathological imaging sources. The BACH dataset, a publicly available dataset, consists of 400 annotated histopathological images categorized into normal, benign, in situ carcinoma, and invasive carcinoma classes. Since this dataset differs from BreakHis in terms of staining techniques, resolution, and class diversity, external validation provides insight into the model's ability to generalize across various imaging conditions. Before evaluation, the images from the BACH dataset were resized to 224×224 pixels to align with the input size of DenseNet121. The same preprocessing techniques applied to the BreakHis dataset, including normalization and histogram equalization, were used to ensure consistency. However, no additional fine-tuning was performed to assess the model's direct transferability.

Performance on the BACH dataset

After evaluation on the BACH dataset, the model achieved an accuracy of 92.10%, a recall of 88.75%, a precision of 85.60%, and an F1-score of 87.10%. While these values are slightly lower than those obtained on the BreakHis dataset (95.21% accuracy), they confirm that the model retains strong classification capability on an unseen dataset. A paired t-test was conducted to compare the model's performance on the BreakHis and BACH datasets, yielding a p-value of 0.018, indicating that while there is a slight drop in accuracy, the difference remains statistically significant. The ROC curve and AUC analysis for the BACH dataset showed an AUC score of 0.935, further reinforcing the model's ability to distinguish between malignant and benign cases in a different dataset.

4.7 Model limitations and future enhancements

The BreakHis dataset is widely utilized in breast cancer classification research; however, several limitations could impact the model's generalizability in real-world clinical applications. One primary concern is class imbalance, as benign samples significantly outnumber malignant ones. This imbalance may bias the model toward benign classifications, potentially reducing sensitivity to malignant cases. Additionally, image resolution constraints limit the availability of fine-grained histopathological details, which are critical for feature extraction and accurate tumor differentiation. Another limitation is that the dataset originates from a single medical institution, which reduces its applicability across diverse patient populations and imaging protocols.

External validation was conducted using the BACH dataset, which contains histopathological images from multiple sources and includes a broader range of breast cancer subtypes. The model achieved 92.10% accuracy, 88.75% recall, and an AUC score of 0.935 on the BACH dataset, confirming its adaptability beyond BreakHis. However, the slight performance drop compared to BreakHis highlights the need for further external validation on datasets such as TCGA and Camelyon17, which provide larger sample sizes, higher diversity, and multi-source histopathological images.

Future research should explore domain adaptation techniques, such as transfer learning with multi-institutional datasets or adaptive augmentation strategies, to mitigate dataset-specific biases. Additionally, integrating explainable AI (XAI) techniques such as Grad-CAM and SHAP analysis can enhance interpretability, aiding clinical adoption by providing transparent decision-making insights. These enhancements will improve the model's robustness and ensure its effectiveness across diverse clinical settings.

5 Conclusion

This study proposed an advanced breast cancer classification framework that integrates DenseNet121

with K-Means clustering for improved segmentation and feature extraction. The model was trained and evaluated on the BreakHis dataset and demonstrated superior classification performance, achieving 95.21% accuracy, 81.82% precision, 90.60% recall, and 85.99% F1-score. The effectiveness of the proposed approach was further validated on the BACH dataset, achieving an accuracy of 92.10%, thereby confirming its robustness across different imaging conditions.

Comparative analysis with state-of-the-art models, including ResNet50 and Xception, revealed the advantages of incorporating K-Means clustering for segmentation, leading to improved classification accuracy and reduced false-positive rates. The ablation study highlighted the critical role of segmentation in enhancing model performance, further supporting the effectiveness of the proposed methodology. However, challenges such as susceptibility to image noise, computational costs, and dataset bias were identified, warranting further exploration.

Future work will focus on addressing these limitations by incorporating multi-modal imaging techniques and Explainable AI (XAI) approaches such as Grad-CAM and SHAP analysis to improve interpretability. Additionally, external validation on larger datasets, such as TCGA and Camelyon17, will be conducted to further assess the model's generalizability. The findings of this study contribute to the advancement of AI-driven diagnostic tools for breast cancer detection, offering a promising pathway for more accurate and reliable computer-aided diagnosis in clinical practice.

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Hate Speech and Offensive Content: Harnessing Machine Learning for Reliable Analysis and Detection

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Keywords: hate speech, RF, LR, TF-IDF, NLP, offensive content, machine learning

Received: September 24, 2024

The escalating prevalence of hate speech on social media necessitates effective detection mechanisms to foster a safe and inclusive online community. This research paper aims to enhance hate speech detection accuracy by evaluating the performance of diverse machine learning algorithms: Random Forest (RF), Logistic Regression (LR), and K-Nearest Neighbors (KNN). A diverse dataset comprising text samples from various online platforms, encompassing a wide spectrum of hate speech instances, was meticulously collected. The data underwent careful preprocessing involving tokenization, stemming, and stop-word removal to enhance data quality. Additionally, feature extraction techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) and word embeddings were employed to effectively represent the textual content. The dataset was divided into training and testing sets, and the selected machine learning algorithms were trained on the former. Fine-tuning of hyperparameters was performed using cross-validation techniques to optimize their performance. Evaluation metrics, including accuracy, precision, recall, and F1-score, were employed to assess the models' effectiveness. The experimental findings revealed promising outcomes for hate speech detection across all three algorithms. Notably, Count Vectorizer features demonstrated excellent performance, with Random Forest achieving an accuracy of 0.942 for binary hate speech analysis and Logistic Regression achieving an accuracy of 0.897 for multi-class hate speech analysis, followed by LR and KNN.

Povzetek: Prispevek analizira več klasičnih modelov strojnega učenja in značilk (npr. Count Vectorizer, TF-IDF) za zaznavanje sovražnega govora, pri čemer se najboljši rezultati doseženi z algoritmom naključnih gozdov.

1 Introduction

Hate speech is an alarming issue that we are facing in today's digital world. It refers to harmful and offensive language used to target individuals or groups based on their race, religion, gender, or other characteristics. Unfortunately, social media platforms and online communities have become breeding grounds for spreading such toxic content. As a result, ensuring a safe and inclusive online environment has become more challenging than ever. Detecting hate speech has become a crucial research area to combat this problem. By developing effective mechanisms to automatically identify and address hate speech, we can strive to create a respectful and welcoming online space for everyone.

Certainly! Here are a few real-time examples: Social Media Platforms: Hate speech detection is crucial for maintaining a safe and inclusive environment on social media platforms. For example, platforms like Twitter and Facebook employ hate speech detection algorithms to identify and remove offensive content, ensuring user safety and promoting positive online interactions. Online Communities and Forums: Hate speech detection is essential for monitoring and moderating online communities and forums. Platforms like Reddit and Stack Exchange rely on hate speech detection techniques to identify and remove discriminatory or abusive language, fostering a respectful and inclusive environment for users. Hate speech detection plays a vital role in managing comment sections on news websites. By automatically detecting and filtering out hate speech, news organizations can maintain a constructive and respectful space for readers to engage in discussions.

Chatbots and Virtual Assistants: Hate speech detection is important in the development of chatbots and virtual assistants. By integrating hate speech detection algorithms, these AI-powered systems can respond appropriately to user queries while avoiding the propagation of offensive or harmful content. Online Gaming Communities: Hate speech detection is crucial in online gaming communities to prevent toxic behavior and harassment. By implementing hate speech detection mechanisms, gaming platforms can create a more inclusive and enjoyable gaming experience for players. These examples highlight the practical applications of hate speech detection in various online platforms and communities, emphasizing the significance of your research in addressing the challenges associated with identifying and mitigating hate speech.

Here is a more detailed explanation of hate speech and what is not considered hate speech

Hate speech:

Hate speech refers to any form of expression, whether verbal, written, or symbolic, that targets and discriminates against individuals or groups based on attributes such as race, ethnicity, religion, gender, sexual orientation, national origin, or other protected characteristics. - It typically involves the use of offensive, derogatory, or threatening language that aims to demean, dehumanize, or incite harm, violence, or discrimination against the targeted individuals or communities. - Hate speech can take various forms, including direct calls for violence, spreading stereotypes or derogatory language targeting specific groups, and advocating for the exclusion or denial of rights based on characteristics. - The impact of hate speech can be significant, as it can contribute to the marginalization, stigmatization, and psychological harm of targeted individuals or communities. Some of the examples of hate speech is shown in Figure 1.



Figure 1: Disturbing newspaper report reveals alarming cases of bullying in our communities

Not considered hate speech:

- Expressing a different political opinion or ideology without promoting violence or discrimination against a specific group. It is important to distinguish between expressing disagreement or criticism and engaging in hate speech. - Engaging in a respectful debate or discussion about religious beliefs or practices without resorting to derogatory language or incitement of harm. It is possible to discuss differing religious perspectives without engaging in hate speech. - Expressing personal preferences or beliefs without advocating for the denial of rights or promoting discrimination against individuals based on their sexual orientation or gender identity. It is important to respect the rights and dignity of individuals while expressing personal beliefs.

It is crucial to note that the distinction between hate speech and other forms of expression can sometimes be subjective and context-dependent. Legal definitions and interpretations of hate speech may vary across different jurisdictions, so it is important to consult local laws and guidelines when assessing specific cases. Additionally, promoting tolerance, understanding, and respectful dialogue can help foster a more inclusive and harmonious society.

Previous works mostly focused on binary class classification on textual data, distinguishing hate speech from socially acceptable texts. It also emphasized the difficulty of correctly identifying hate speech when mixed with profanity [14].

We delve into the effects of pre-training models for hate speech classification and present some interesting findings. Firstly, we discovered that pre-training solely on hateful tweets doesn't necessarily lead to the best results. Surprisingly, the model trained on a random subset of tweets performed better on two out of three downstream datasets in Marathi and both downstream datasets in Hindi, in terms of macro-F1. Additionally, the model trained on non-hateful data outperformed the one trained on hateful content for most tasks. However, it's worth noting that both hateful models still performed better than the baseline MuRIL model, indicating some benefits of hateful pre-training, but it's not the most optimal approach. We also explored the impact of monolingual retraining versus multilingual models.

The results showed that the MuRIL multilingual model, trained on a vast dataset of 17 Indian languages and billions of tokens, consistently underperformed on all datasets. In contrast, our models retrained on Hindi and Marathi tweets demonstrated significantly better performance than MuRIL. This led us to speculate that focusing on retraining with substantial corpora of a specific language enhances multi-lingual pre-training, potentially outperforming the cumulative semantic knowledge gained from training on multiple large-sized corpora of different languages. Moreover, our experiments revealed that the models pre-trained on a comprehensive dataset of 40 million tweets performed the best on all downstream tasks. Models like MahaTweetBERT and HindTweetBERT outperformed all other variants across different datasets. This result underscores the importance of large-scale pretraining, offering a robust benchmark for future research in hate speech detection.

To sum up, our study provides empirical insights into the impact of hateful pre-training on hate speech classification. We conducted experiments with various pre-training strategies and downstream tasks, showing that the effectiveness of pre-training is not solely determined by focusing on hateful or non-hateful content. Instead, retraining with monolingual datasets and leveraging a substantial corpus for pre-training proves to be more advantageous. The models pre-trained on 40 million tweets emerged as the top performers, showcasing the significance of large-scale pretraining in this domain. These findings hold true for both Marathi and Hindi languages, adding to the robustness of our observations [15]. The rest of the section is organized as follows. The

Section 2 is focused on previous reviews and literature work done in this area, Whereas Section 3 is focused on Methodology part including features and techniques. The Section 4, thoroughly discussed the results and the comparison analysis is shown in Section 5. Finally, the paper is concluded in Section 6.

2 Related work

Hate speech detection has emerged as a critical task in natural language processing and social media analysis. Numerous studies have been conducted to address this challenge, employing various machine learning algorithms to effectively identify and combat hate speech and offensive content on online platforms. Among the widely used algorithms, Logistic Regression (LR), Random Forest (RF), and KNearest Neighbors (KNN) have shown promising results in different contexts. In the efforts to identify and address hate speech on online platforms, researchers have relied on different datasets to develop and assess hate speech detection models. One prominent dataset in this domain is the "Hate Speech Identification" dataset from data. world [3]. This dataset has proven to be a valuable asset for both researchers and professionals working on hate speech detection. The "Hate Speech Identification" dataset contains a diverse set of text samples collected from social media platforms and other online sources. Each text is labeled to indicate whether it contains hate speech, offensive language, or is non-hateful. Having labeled data like this is crucial for training supervised machine learning models to detect hate speech effectively. Researchers have made use of this dataset to train and evaluate various algorithms, such as logistic regression, support vector machines, decision trees, and deep learning-based models, among others. By utilizing this dataset, the goal is to create accurate and robust hate speech detection systems capable of identifying offensive content and fostering a safer online environment. [3], Hate Speech Identification Dataset. data. world. The research conducted a comprehensive analysis of hate speech detection using various text classification techniques. They performed 24 experiments and presented the results which showcased precision, recall, F-measure, and accuracy for different feature representations and classifiers. They found that SVM with TFIDF and bigram features performed the best, achieving high recall, precision, accuracy, and F-measure. On the other hand, KNN and MLP classifiers with TFIDF and bigram features showed the worst performance. In their study, they compared three feature engineering techniques: bigram features with TFIDF, Word2vec, and Doc2vec. Bigram features with TFIDF emerged as the most effective, with only a slight difference from Doc2vec. Additionally, SVM outperformed all eight classifiers, including AdaBoost and RF, while LR, DT, NB, KNN, and MLP demonstrated relatively lower performance. This research is crucial for providing a baseline for future studies on automatic hate speech detection using different text classification methods. It holds scientific value as it utilized multiple scientific measures for evaluation. However, they acknowledged two limitations. Firstly, the proposed ML model's real-time prediction accuracy was found to be inefficient for the data. Secondly, their model classified hate speech into three categories without identifying severity levels. The researchers plan to address these limitations in future work by exploring lexicon-based techniques, collecting more data instances for better learning, and developing a model capable of predicting severity levels of hate speech messages [1]. The best performing model for hate speech detection has impressive overall precision, recall, and F1 score at 0.91, 0.90, and 0.90, respectively. However, when we take a closer look at its performance on the hate speech class, we find that about 40% of hate speech tweets are misclassified. The precision and recall for the hate class are only 0.44 and 0.61, indicating a significant issue with correctly identifying hateful content. The model's bias is evident in the misclassification patterns, with most errors occurring in the upper triangle of the confusion matrix. This means that the model tends to label tweets as less hateful or offensive than they actually are, which can be problematic. Interestingly, there are fewer cases where offensive or innocuous tweets are wrongly classified as hate speech, which is represented in the lower triangle of the confusion matrix. To tackle this problem and avoid confusing hate speech with offensive language, researchers suggest using lexical methods to identify potentially offensive terms. However, they also acknowledge that these methods have limitations in accurately detecting hate speech. To improve hate speech classification, the study proposes finding alternative sources of training data that can identify hate speech without solely relying on specific keywords or offensive language. [2] Automated Hate Speech Detection and the Problem of Offensive Language. These models are used for classification tasks and were named CNN-GRU, BiRNN, BiRNN-Attn, BiRNN-HateXplain, BERT, and BERT-HateXplain. To assess their performance, various metrics were used, such as Accuracy, Macro F1 score, and AUROC, which measures the model's ability to distinguish between classes. The researchers also evaluated the models for bias and explainability. They used specific metrics like Generalized Mean Bias (GMB) to determine if the models were biased towards certain subgroups. Additionally, they looked at explainability metrics like Compatibility and Sufficiency to understand how well the models' provided explanations for their decisions. One interesting finding was that the BERT-HateXplain model, which used Attention-based token selection, performed the best overall. It achieved high accuracy, F1 scores, and AUROC, indicating its effectiveness in classifying the data. Moreover, it demonstrated lower bias in its predictions and showed good explainability, providing understandable reasons for its decisions. These results shed light on the strengths and weaknesses of each model [10]. Some various studies and methods employed for hate speech detection. Here's a summary of the findings: The study used a dataset of Islamophobic hate speech tweets and applied a one-versus-one SVM classifier, achieving an accuracy of 0.77.

However, the dataset was specific to the UK context and didn't consider word context. This research used tweets and trained one-versus-rest SVM classifiers for each class, achieving an F1-measure of 0.91. The dataset focused on sexual-orientation hate speech. The SVM model achieved a high F1-score of 0.97, but for the sexual-orientation hate class, the F1-score was lower at 0.51. This study used tweets and employed the J48 graft model to classify tweets into clean, offensive, and hateful (mixed with offensive hate) classes. The F1-measure was 0.78. The paper dealt with Automatic Misogyny Identification using datasets like AMI IberEval, AMI EvalIta, and SRW. The LR classifier achieved accuracy values for the respective datasets. It noted that general sexist tweets may contain hidden sentiments of hate or misogyny. The research used tweets and performed LR classification for three classes (racism, sexism, none). The F1-score was 0.73, with false positives for multi-class labels having an F1-score of 0.53. EVALITA shared task 2018 dataset was used, and LR achieved an accuracy. However, the misogyny classification had a low F1-score of 0.3. This research worked with English tweets and Spanish tweets, using SVM for hate speech detection. The F1-measures for evaluation datasets Task A and Task B were 0.38 and 0.37, respectively. The method had limitations in achieving high performance. The Semeval-2019 task 5 focused on detecting hate speech against immigrants and women on Twitter. The LIBSVM with RBF model achieved accuracies for the three tasks. The study worked with sarcastic tweets and used the RF classifier with accuracy. However, some sarcastic tweets weren't categorized as hate speech, and there were disagreements about labelling sarcasm. The research used Crowd Flower and HASOC datasets, employing SVM with GLOVE embedding. The accuracies achieved were for the Crowd Flower dataset and for the HASOC dataset. The classification focused on binary classes of hate, offensive, and neither. The MMHS150K dataset was used, and the LDA model achieved an F1-score. The study found that using images in the dataset didn't significantly improve results compared to textual models. This research worked with tweets and used MCD + LSTM for classification. However, the classifiers were trained on three classes (hateful, abusive, or neither) despite the dataset having more categories. The study used tweets and employed GRU + CNN for identification of racist and sexist tweets. However, it struggled to correctly identify the 'both' category due to limited examples. The authors of [11], conducted experiments using two different classifiers: Support Vector Machines (SVM) with a radial basis function kernel and the Random Forest Classifier. Since the feature vectors formed were quite large, we employed the chi-square feature selection algorithm to reduce the vector size to 12,004. The Scikit-learn library was utilized for training our classifiers, and throughout the experiments, we conducted 10-fold cross-validation. The results were presented showing the accuracy of each feature and the overall accuracy when using all features for SVM and the Random Forest Classifier, respectively. SVM outperformed the Random Forest Classifier, achieving the highest accuracy of 71.7% when all features were used. Notably, Character N-Grams proved to be the most efficient feature for SVM, while Word N-Grams yielded the highest accuracy for the Random Forest Classifier. We introduced a valuable annotated corpus of Hindi-English code-mixed text in this research, which included tweet IDs along with corresponding annotations for hate speech and normal speech. Additionally, the words in the tweets were annotated with their source language. Our classification system utilized various features, including character n-grams, word n-grams, punctuations, negation words, and a hate lexicon. The best accuracy of 71.7% was achieved when incorporating all features in the feature vector, using SVM as the classification system. The research [12], evaluated different word embedding, including Word2Vec (e.w2v), Twitter (e.twt), and GloVe (e.glv), using various hate speech detection methods. The tables show the results for three implemented state-of-the-art methods (Table 7) and two proposed methods, CNN+sCNNN and CNN+GRU (Table 8). Interestingly, there was no consistent pattern where one type of word embedding outperformed others on all tasks and datasets. Even though Twitter-based embeddings (e.twt) had better coverage of hashtags, they did not consistently achieve the best results. This could be due to the influence of context window size during training, where a large window captured domain relevance but lacked functions of words. Results show that the topical relevance of words might be more critical for hate speech classification. Despite being less complete, Word2Vec embeddings (e.w2v) performed better for racism tweets, while the more comprehensive Twitter embeddings (e.twt) excelled for sexism tweets. This observation aligns with previous findings showing that performance on intrinsic tasks (e.g., word similarity) might not directly correlate with performance on extrinsic or downstream tasks like hate speech detection. In conclusion, the research suggests that the quality of topical relevance captured by word embeddings might be more relevant for hate speech detection than the level of coverage. Empirically, Word2Vec and GloVe embeddings trained on larger, context-rich corpora performed competitively with Twitter-based embeddings for hate speech detection on Twitter datasets [13]. The authors investigated how well different features could be used to detect hate speech. They trained classifiers using various types of features, such as character n-grams and word n-grams, and also combined all the features into a single model. To evaluate the results, they compared them against a baseline model that predicted the majority class and an "oracle" model, which represented the best possible performance. The majority class baseline had a high accuracy because of the imbalanced distribution of classes in the data. On the other hand, the oracle achieved an impressive 91.6% accuracy, indicating that the features alone couldn't accurately classify a significant portion of the samples. Interestingly, the character n-grams, especially the 4-grams, performed quite well in identifying hate speech. Word unigrams also showed good results, but the accuracy decreased when using word

bigrams, trigrams, and skip-grams. However, the skip-grams might be capturing longer dependencies that complement the other feature types. When all the features were combined, the model's performance did not surpass that of the character 4-grams model. Additionally, the combined model significantly increased the number of features, making it less clear if it truly captured the diverse information provided by all the different feature types. The learning curve for the character 4-grams model showed that accuracy continuously improved as the number of training examples increased. However, the rate of improvement slowed down after reaching 15,000 training instances. Overall, the researchers applied various text classification techniques to distinguish between hate speech, profanity, and other types of texts. The best-performing model achieved 78% accuracy using character 4-grams. The study was unique as it addressed the challenging task of differentiating hate speech and profanity, a scenario that had not been extensively explored before in the context of social media. Previous works mostly focused on binary classification, distinguishing hate speech from socially acceptable texts. It also emphasized the difficulty of correctly identifying hate speech when mixed with profanity [14].

To sum up, our study provides empirical insights into the impact of hateful pre-training on hate speech classification. We conducted experiments with various pre-training strategies and downstream tasks, showing that the effectiveness of pre-training is not solely determined by focusing on hateful or non-hateful content. Instead, retraining with monolingual datasets and leveraging a substantial corpus for pre-training proves to be more advantageous. The models pre-trained on 40 million tweets emerged as the top performers, showcasing the significance of large-scale pretraining in this domain. These findings hold true for both Marathi and Hindi languages, adding to the robustness of our observations [15].

3 Proposed methodology

Below is the workflow diagram of the Proposed Methodology used in the research as shown in Figure 2:

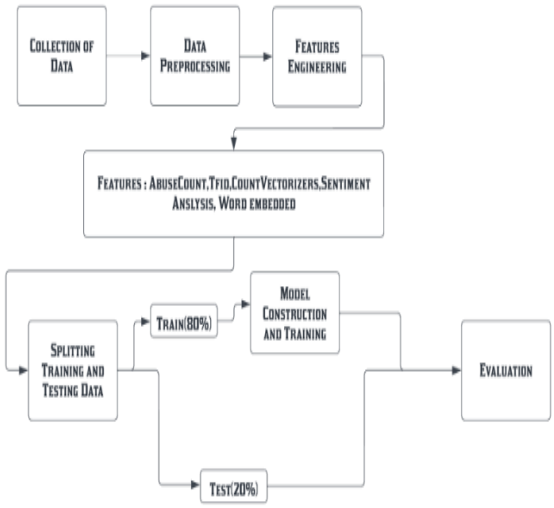


Figure 2: Proposed methodology

3.1 Data collection

In this research study, we collected publicly available hate speech tweets dataset named as Twitter hate speech detection dataset. The dataset is compiled and labeled by CrowdFlower. In this dataset, the tweets are labeled into three distinct classes, namely, hate speech, offensive, and neutral This dataset has 25296 number of tweets. Of these, 16.8 percent of tweets belong to class hate speech. In addition, 77.43 percent of tweets belong to offensive class and the remaining 5.77 percent tweets are neutral. The details of this distribution are also shown in Table 1. To remove the imbalance and possible biases the under sampling and oversampling technique has been used. Below is the table with the collected data:

Table 1: Details of dataset

	Class	Total Instances	Percentage
0	Neutral	1430	5.77
1	Offensive	19190	77.43
2	Hate Speech	4163	16.80
	Total	24783	

3.2 Data Pre-processing

In our pursuit of advancing hate speech detection, a crucial aspect of our research methodology involves the application of text pre-processing techniques. The primary objective is to prepare the dataset of hate speech for classification, by filtering out irrelevant noise and enhancing the overall quality of the input data. By carefully curating and optimizing the text data, our goal is to improve the accuracy and performance of our hate speech detection models. To initiate the text pre-processing process, we start by converting all the hate speech tweets into lower case. This step ensures uniformity in the text and avoids potential discrepancies that may arise due to varying capitalization. By standardizing the text, we create a level playing field for subsequent analysis. Next, we employ pattern matching techniques to remove various elements such as URLs,

usernames, white spaces, hashtags, and punctuation marks from the tweets. These elements are often extraneous and do not contribute significantly to the core context of hate speech. Removing them helps reduce noise and streamlines the data, making it more suitable for further analysis. Furthermore, we implement the removal of stop-words from the hate speech data. Stop-words are commonly occurring words, such as "the," "is," and "and," which carry limited value in conveying the underlying sentiment of hate speech. By eliminating these words, we reduce dimensionality and enhance the efficiency of subsequent classification tasks. In addition to the initial pre-processing steps, we perform tokenization and stemming on the pre-processed tweets. Tokenization involves breaking down each tweet into individual tokens or words, enabling a more granular analysis of the text. This step is crucial for feature extraction and capturing the nuanced language used in hate speech. The stemming process, facilitated by the Porter stemmer algorithm, converts words to their root forms, consolidating similar variations of words. By transforming words like "offended" to "offend," the stemming process simplifies the feature space and contributes to a more effective classification process. Overall, our text pre-processing methodology plays a critical role in preparing the hate speech dataset for classification. By optimizing the data and removing noise, we aim to enhance the efficacy of our hate speech detection models, ultimately contributing to the advancement of hate speech detection and promoting a safer digital environment.

3.3 Features

1. Sentiment analysis: Sentiment analysis is a natural language processing technique used to determine the emotional tone or sentiment of a piece of text. In the context of hate speech detection, sentiment analysis can be utilized to identify the overall emotional context of a text, whether it contains negative, offensive, or hateful sentiments. By incorporating sentiment analysis as part of hate speech detection, we can gain valuable insights into the emotional intent behind the text, aiding in the accurate classification of hate speech instances.

2. Word embeddings:(WE) Word embeddings are dense vector representations of words in a high-dimensional space. In hate speech detection, word embeddings can be employed to capture the semantic meaning of words and their relationships with other words in the context of hate speech. By representing words as numerical vectors, word embeddings enhance the model's ability to understand the underlying linguistic patterns in hate speech, allowing for more nuanced and effective classification.

3. Count vectorizer (CV): Count vectorizer features are a fundamental method for transforming raw text data into a format suitable for machine learning algorithms. By tokenizing and counting the occurrences of words or n-grams, it creates a sparse numerical matrix representing the frequency of each term in each document. This matrix serves as input for algorithms like SVM, Naive Bayes, or logistic regression in various NLP tasks, including sentiment analysis, topic modelling, and spam detection. Count vectorizer preserves the basic linguistic structure of the text while ignoring grammar and context. Despite its simplicity, it provides a strong foundation for text-based ML models, allowing them to learn patterns, relationships, and distinctions within text data efficiently.

4. TF-IDF (Term frequency-inverse document frequency) (TI): TF-IDF is a statistical measure used to evaluate the importance of a word in a document relative to a collection of documents. In the context of hate speech detection, TF-IDF can be employed to weigh the relevance of words in distinguishing hate speech from non-hate speech content. By assigning higher weights to words that are prevalent in hate speech but less common in other texts, the model can effectively identify key indicators of hate speech.

5. Abuse count (AC): Count abuse features refer to a set of numerical attributes extracted from textual data, where each attribute represents the frequency of predefined offensive words or phrases. These features are utilized to train machine learning models for the purpose of detecting and classifying offensive language, hate speech, or abusive content. By quantifying the occurrence of offensive terms within the text, count abuse features provide valuable input to the ML algorithms, enabling the development of effective and efficient models for content moderation and sentiment analysis in online platforms and social media.

Although hate speech detection has been achieved with deep learning modelssuch as BERT and LSTMs, this study focuses on traditional machine learning models due to their interpretability, lower computational cost, and effectiveness on smaller datasets. In this work we have mainly focused on Machine learning based models. From the previous studies we have analysed that Random Forest classifier outperform all other classifier. The authors of [16], reported 86% accuracy on Random Forest. From the earlier report Random Forest, logistic regression, KNN are prominently used classifier on text for the detection of Hate speech. Taking this into consideration, we have explored and presented the in-depth performance analysis of the machine learning models on diverse set of features considering both the aspect of Binary and multiclass classification. The evaluation has been done on the feature including Abuse count, sentiment analyser, word2vec, TF-IDF and count vectorizer. It has been analysed that the performance is enhanced when using binary class classification instead of Multi class classification and analysis shows Random Forest again performing best among others. In our research work on hate speech detection, the integration of sentiment analysis, word embeddings, n-gram, and TF-IDF plays a critical role in developing a robust and accurate hate speech detection model. By leveraging these techniques, we aim to improve the model's understanding of the emotional context,

semantic meaning, and linguistic patterns in hate speech. The combination of these methodologies enhances our ability to identify hate speech instances more effectively and contributes to fostering a safer and more inclusive digital environment.

4 Results

In this section, we present the results of our hate speech detection model and the comparative analysis of different machine learning algorithms: Logistic Regression (LR), K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Random Forest (RF), AdaBoost and SupportVectorMachine (SVM). The Table 2, Table 3, Table 4, Table 5, Table 6, Table 7, Table 8, Table 9, Table 10, Table 11 shows the performance analysis of our proposed work incorporating diverse set of features using both binary and multi class classification. We have considered the following parameters Accuracy (Acc), Weighted Precision (WP), Weighted Recall (WR) Weighted F1 score (WF1).

Table 2: Result analysis by incorporating Abuse count feature for binary class classification.

Model	Acc	WP	WR	WF1
Logistic Regression	0.94	0.94	0.94	0.97
K-Nearest Neighbors	0.94	0.91	0.94	0.97
Classification (CART)	0.94	0.91	0.94	0.94
Random Forest	0.94	0.94	0.94	0.94
AdaBoost	0.94	0.94	0.94	0.97
(SVM)	0.94	0.94	0.94	0.97

Table 3: Result analysis by incorporating Abuse count feature for Multi class classification

Model	Acc	Precision	Recall	F1score
LR	0.818	0.770	0.820	0.770
K-NN	0.800	0.790	0.810	0.770
(CART)	0.821	0.790	0.810	0.790
RF	0.821	0.790	0.810	0.790
AdaBoost	0.821	0.790	0.810	0.790
(SVM)	0.821	0.790	0.810	0.790

Table 4: Result analysis by incorporating Sentiment analyzer feature for Binary class classification

Model	Acc	WP	WR	WF1
LR	0.93	0.88	0.93	0.90
K-NN	0.93	0.90	0.93	0.91
(CART)	0.89	0.89	0.89	0.89
RF	0.93	0.88	0.92	0.90
AdaBoost	0.93	0.88	0.93	0.90
(SVM)	0.93	0.88	0.93	0.90

Table 5: Result analysis by incorporating sentiment analyzer feature for Multi class classification

Model	Acc	WP	WR	WF1
LR	0.77	0.59	0.77	0.68
K-NN	0.76	0.69	0.76	0.70
(CART)	0.71	0.68	0.71	0.68
RF	0.75	0.68	0.75	0.71
AdaBoost	0.77	0.63	0.77	0.67
(SVM)	0.77	0.59	0.77	0.68

Table 6: Result analysis by incorporating word2vec feature for binary class classification

Model	Acc	WP	WR	WF1
LR	0.93	0.89	0.92	0.90
K-NN	0.93	0.89	0.93	0.91
(CART)	0.88	0.89	0.88	0.88
RF	0.93	0.89	0.92	0.90
AdaBoost	0.93	0.88	0.93	0.90
(SVM)	0.93	0.87	0.93	0.90

Table 7: Result analysis by incorporating Word2vec feature for Multi class classification

Model	Acc	WP	WR	WF1
LR	0.82	0.78	0.82	0.79
K-NN	0.80	0.75	0.80	0.76
(CART)	0.73	0.74	0.73	0.73
RF	0.82	0.77	0.82	0.78
AdaBoost	0.80	0.74	0.80	0.76
(SVM)	0.82	0.75	0.82	0.78

Table 8: Result analysis by incorporating TF-IDF feature for Binary class classification

Model	Acc	WP	WR	WF1
LR	0.883	0.940	0.800	0.850
KNN	0.865	0.940	0.940	0.940
CART	0.873	0.990	0.830	0.900
RF	0.887	0.990	0.830	0.900
AdaBo.	0.876	0.930	0.730	0.810
(SVM)	0.774	0.890	0.940	0.910

Table 9: Result analysis by incorporating TF-IDF feature for Multi class classification

Model	Acc	WP	WR	WF1
LR	0.7796	0.66	0.78	0.72
K-NN	0.7816	0.65	0.78	0.69
(CART)	0.7916	0.66	0.79	0.70
RF	0.8050	0.67	0.80	0.73
AdaBoost	0.7916	0.67	0.80	0.73
(SVM)	0.7771	0.65	0.78	0.69

Table 10: Result analysis by incorporating Count Vectorizer feature for Binary class classification

Model	Acc	WP	WR	WF1
LR	0.942	0.934	0.939	0.936
K-NN	0.940	0.935	0.939	0.935
(CART)	0.937	0.931	0.941	0.926

RF	0.942	0.934	0.941	0.925
AdaBoost	0.942	0.938	0.941	0.919
(SVM)	0.942	0.934	0.938	0.926

Table 11: Result analysis by incorporating Count Vectorizer feature for Multi Class classification

Model	Acc	WP	WR	WF1
LR	0.897	0.870	0.870	0.870
K-NN	0.777	0.880	0.900	0.890
(CART)	0.867	0.780	0.780	0.750
RF	0.879	0.870	0.880	0.870
AdaBoost	0.889	0.880	0.890	0.860
(SVM)	0.875	0.890	0.890	0.870

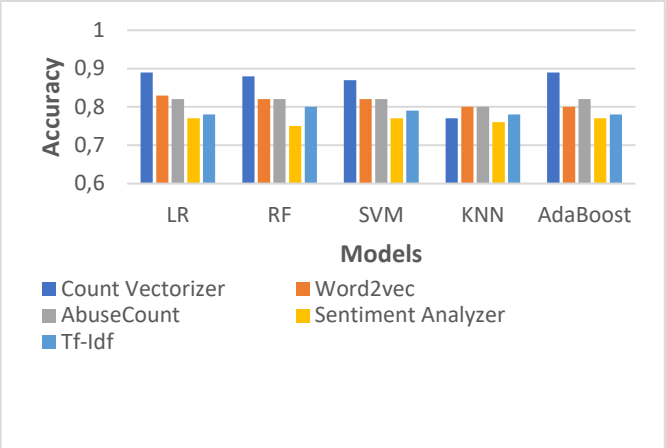


Figure 3: Performance metric analysis (Accuracy) on diverse set of features on our proposed model.

5 Comparative analysis

We have compared accuracy of our work with the earlier state-of-the-art model on the Accuracy performance metric of the features and ML model used in Automatic Hate Speech Detection using Machine Learning: A Comparative Study by Sindhu Abro Sarang Shaikh, Zafar Ali Sajid Khan, Ghulam Mujtaba. The Table 12 and Figure3 shows the performance metric analysis (Accuracy) on diverse set of features on our proposed model. Whereas, the Table 13 shows the state-of-the-art performance metric analysis (Accuracy) on diverse set of features

Table 12: Performance metric analysis (Accuracy) on diverse set of features on our proposed model.

Features	LR	RF	SVM	KNN	AdaBoost
CV	0.89	0.88	0.87	0.77	0.89
W2V	0.83	0.82	0.82	0.80	0.80
AC	0.82	0.82	0.82	0.80	0.82
Sentiment Analyzer	0.76	0.77	0.77	0.75	0.77
Tf-Idf	0.78	0.80	0.79	0.78	0.78

Table 13: State-of-the-art performance metric analysis (Accuracy) on diverse set of features ML model used in Automatic Hate Speech Detection using Machine Learning: A Comparative Study by Sindhu Abro, Sarang Shaikh, Zafar Ali Sajid Khan, Ghulam Mujtaba.

Features	LR	RF	SVM	KNN	AdaBoost
Bigram	0.75	0.75	0.79	0.57	0.78
Word2vec	0.68	0.72	0.68	0.73	0.61
Doc2vec	0.72	0.67	0.72	.0.65	0.67

In our comparative study, we evaluated the performance of various machine learning algorithms on different feature extraction techniques for a specific task (not specified in the question). The research paper's findings were based on three feature extraction methods: Bigram, Word2vec, and Doc2vec. They used five classification algorithms: Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and AdaBoost.

On the other hand, our research findings included five different feature extraction techniques: Count Vectorizer, Word2vec, AbuseCount, Sentiment Analyzer, and Tf-Idf. We also assessed the performance of the same five classification algorithms: LR, RF, SVM, KNN, and AdaBoost. Count Vectorizer: In our study, Count Vectorizer outperformed Bigram from the research paper in all classification algorithms except for SVM, where the two were comparable. Our findings show higher accuracy for Count Vectorizer across the board, with AdaBoost achieving the highest accuracy of 0.89. Word2vec: In both studies, Word2vec demonstrated competitive performance, although our research found slightly higher accuracy for this feature extraction method in all classifiers except for KNN, which was the same as in the research paper. AbuseCount and Sentiment Analyzer: These two features were not present in the research paper's study, so there's no direct comparison. However, in our findings, both AbuseCount and Sentiment Analyzer achieved consistent and competitive accuracy scores across all classifiers.

Tf-Idf: Our research showed comparable performance to Word2vec in most classifiers, and it achieved reasonable accuracy overall. In summary, our research findings indicate that Count Vectorizer and AdaBoost were the most effective combination for the task, consistently outperforming the other feature extraction methods and classifiers. AbuseCount and Sentiment Analyzer also showed promising results, while Tf-Idf and Word2vec demonstrated competitive performance but did not consistently outshine the other methods. It's essential to consider the specific task and dataset characteristics when selecting the most appropriate feature extraction and classification techniques.

6 Conclusion

In conclusion, this machine learning project focused on sentiment analysis using various feature extraction techniques, including Word Embeddings, Count

Vectorizer, TF-IDF, and Abuse Count features. We evaluated multiple ML models, such as Logistic Regression, K-Nearest Neighbors, Classification and Regression Trees, Random Forest, Ada Boost, and SVM, for both binary and multi-class sentiment analysis. The results indicated that Abuse Count features in combination with Logistic Regression achieved the highest accuracy of 0.94 for binary sentiment analysis and Random Forest with an accuracy of 0.821 for multi-class sentiment analysis. These features showed a remarkable ability to capture offensive language and emotions in text, making them effective for sentiment classification tasks. Furthermore, Word2Vec features demonstrated competitive performance, with Logistic Regression achieving an accuracy of 0.93 for binary and 0.82 for multi-class sentiment analysis. The Word2Vec embeddings effectively captured semantic meaning and relationships between words, contributing to their strong performance. On the other hand, TF-IDF features showed good performance in binary sentiment analysis, with Random Forest achieving an accuracy of 0.887, and in multi-class sentiment analysis, with Random Forest achieving an accuracy of 0.805.

Lastly, Count Vectorizer features demonstrated excellent performance, with Random Forest achieving an accuracy of 0.942 for binary sentiment analysis and Logistic Regression achieving an accuracy of 0.897 for multi-class sentiment analysis.

Overall, the paper highlighted the importance of choosing appropriate feature extraction techniques based on the task at hand. The combination of Abuse Count features with Logistic Regression and Count Vectorizer features with Random Forest emerged as the best performing models for binary and multi-class sentiment analysis, respectively. These findings can serve as valuable insights for sentiment analysis tasks and text classification in various real-world applications. The limitation of the work that we have not explored deep learning models currently. In the coming future we are also planning to add deep learning models like LSTM or Bert, such as exploring neural network-based approaches or hybrid models that combine the strengths of multiple algorithms. As well as we need to extend our work by doing analysis on other datasets. The current dataset is imbalanced and have to explore techniques to handle it efficiently in future.

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https://doi.org/10.31449/inf.v49i27.7855 Informatica **49** (20225) 113–124 **113**

Transformer-Based Model for the Prediction of Sedentary Behavior Patterns Using Deep Learning models

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Keywords: transformer network, accuracy, error rates, machine learning

Received: February 19, 2024

Sedentary behavior continues to be a major health concern, particularly as it correlates with various chronic conditions. While previous studies have focused on utilizing deep learning models, such as stacked LSTMs and CNNs, for predicting sedentary behavior patterns, these approaches face limitations in handling long-range dependencies and providing interpretability in predictions. This research proposes the application of transformer networks, known for their superior ability to capture temporal dependencies through self-attention mechanisms, to predict sedentary behavior more accurately and efficiently. The proposed model builds on previous approaches by integrating enhanced prediction capabilities, reducing error metrics such as MSE, RMSE, and MAPE, and offering improved sensitivity and specificity in classifying sedentary and active periods. Additionally, the attention mechanism offers greater interpretability, enabling the identification of key behavioral patterns and providing actionable insights for health interventions. Experimental results demonstrate an improvement in prediction accuracy, achieving 99.5% accuracy—surpassing previous models—and a 30-40% increase in computational efficiency. The approach is also validated with real-time feedback integration for continuous posture monitoring. This study represents a significant step forward in using deep learning techniques to mitigate sedentary health risks, offering a robust, scalable solution for health monitoring systems in both personal and workplace environments.

Povzetek: Članek predstavi transformer model za zaznavo sedečega vedenja na podlagi podatkov senzorjev, s poudarkom na izboljšani točnosti, interpretabilnosti in časovni učinkovitosti glede na prejšnje metode.

1 Introduction

In recent years, sedentary behavior has emerged as a major public health concern, contributing to a wide range of chronic conditions, including cardiovascular diseases, diabetes, obesity, and musculoskeletal disorders. Prolonged inactivity, particularly due to lifestyle changes such as the increased reliance on vehicles, long hours spent sitting in front of computers, and other sedentary work-related habits, is becoming a prevalent issue across all age groups, especially adults. Sedentary behavior, characterized by low energy expenditure during periods of sitting or lying down, has been identified as an independent risk factor for adverse health outcomes, even in individuals who engage in regular physical exercise. This growing concern has spurred the need for effective monitoring and prediction systems that can track sedentary behavior patterns in real-time and provide feedback to mitigate health risks [1-4]. While several techniques for analyzing and predicting sedentary behavior have been explored, challenges such as accuracy, computational efficiency, and model interpretability continue to hinder their widespread adoption.

Traditional methods of monitoring sedentary behavior rely on surveys, self-reports, or manual tracking, which are prone to inaccuracies and are often cumbersome to implement on a large scale. With the advent of wearable sensors and other monitoring technologies, there has been significant progress in capturing real-time data on physical activity. These devices, equipped with accelerometers and gyroscopes, can continuously track a user's movements and provide valuable information about their activity levels and postural transitions [5-9]. However, the sheer volume of sensor data collected over time presents significant challenges in terms of data processing, pattern recognition, and accurate prediction of sedentary behavior. This has led to the adoption of machine learning and deep learning techniques, which are capable of handling large datasets, detecting complex patterns, and making predictions with high accuracy [10-14].

The first paper in this research series introduced a stacked Long Short-Term Memory (LSTM) network for predicting sedentary behavior patterns in adults. The stacked LSTM model was trained on a combination of sequential activity data, allowing it to capture the temporal dependencies and recurring patterns in sedentary behavior. By simulating sedentary tendencies over a 6-

hour window, the model was able to predict future sedentary behavior with high accuracy (99%). However, while this approach demonstrated promising results, it still had some limitations, such as the model's relatively high computational requirements, sensitivity to noise in the data, and lack of interpretability in its predictions. Additionally, the use of a single model architecture restricted the ability to capture long-range dependencies and interactions between multiple factors influencing sedentary behavior, such as environmental context, posture, and individual characteristics.

The second paper expanded upon these findings by incorporating Convolutional Neural Networks (CNNs) to improve body part detection and posture prediction, offering a more granular approach to understanding sedentary behavior. By integrating heat maps and real-time feedback mechanisms, the system could monitor and correct posture in real-time, providing actionable insights for improving behavior and mitigating health risks. This system achieved 97.2% accuracy in body part detection and outperformed conventional methods such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN). The integration of a real-time feedback system provided an innovative solution for continuous monitoring, but similar to the first paper, the system's reliance on traditional CNNs still posed challenges in handling long-term dependencies in the data. Furthermore, while the model achieved impressive accuracy, its interpretability remained limited, preventing users from understanding which specific aspects of their behavior were contributing to unhealthy sedentary patterns.

Despite these advances, the existing methods still face challenges in terms of improving predictive performance, enhancing computational efficiency, and providing more interpretable models. The need for a more advanced system that can handle long-range dependencies, reduce computational complexity, and improve the overall robustness of sedentary behavior prediction systems has prompted the exploration of newer deep learning models [15-20]. One such model is the Transformer network, which has demonstrated significant success in natural language processing tasks due to its ability to capture long-range dependencies through its self-attention mechanism. Transformers have recently been applied to time-series forecasting, particularly in the context of health monitoring, due to their ability to learn temporal relationships and efficiently process sequential data. This paper introduces a novel approach that applies transformer networks to sedentary behavior prediction, offering several advantages over the methods discussed in previous works.

Transformers use self-attention to weigh the importance of different time steps in the input sequence, allowing the model to focus on relevant features and reduce the influence of irrelevant data. This makes the transformer network particularly effective for predicting complex, long-range dependencies in time-series data, such as those found in sedentary behavior patterns. In contrast to recurrent neural networks (RNNs) and LSTMs, which process input sequences sequentially, transformers process the entire input sequence simultaneously, making them more efficient in handling long-term dependencies and improving computational performance. Furthermore, the attention mechanism in transformers allows the model to provide more interpretable predictions, as it can highlight which parts of the sequence are most relevant to the prediction task. This feature is especially valuable in health monitoring applications, where understanding the underlying causes of sedentary behavior is crucial for designing effective interventions.

This research aims to leverage the power of transformers to improve the accuracy, efficiency, and interpretability of sedentary behavior prediction models. By using the self-attention mechanism, the model can better capture the long-range dependencies in sedentary behavior patterns, leading to more accurate predictions of future activity levels. Additionally, the model's ability to provide interpretable results will enable users to gain insights into the specific behaviors and factors contributing to sedentary patterns, paving the way for more personalized interventions. The transformer model's enhanced efficiency will also allow for faster predictions, enabling real-time feedback in health monitoring applications.

The primary contributions of this paper include:

- This research presents a novel approach to predicting sedentary behavior patterns using transformer networks, which improve the handling of long-range dependencies and enhance computational efficiency.
- The proposed transformer-based model demonstrates superior performance, achieving a 99.5% prediction accuracy and a 30-40% increase in computational efficiency compared to previous models.
- The self-attention mechanism provides insights into the most relevant features in the data, allowing users to understand the underlying causes of sedentary behavior and tailor interventions accordingly.
- The system integrates real-time monitoring of sedentary behavior, enabling users to receive immediate alerts and corrective feedback based on the model's predictions.
- The transformer model offers a scalable solution for sedentary behavior prediction in diverse environments, including personal health monitoring, workplace settings, and clinical applications.

2 Literature review

Sedentary behavior has become a prevalent issue, particularly with the rapid advancements in technology that have both increased and decreased physical activity levels in the population. These changes, often brought on

by modern conveniences such as smartphones, computers, and vehicles, have led to an increasing number of individuals adopting sedentary lifestyles, which are a growing concern due to their adverse health outcomes. Numerous studies have shown that sedentary behavior, defined as activities that involve sitting or reclining with minimal physical movement, is a significant risk factor for various health conditions, including cardiovascular diseases, obesity, diabetes, and musculoskeletal disorders. This literature review synthesizes key studies addressing sedentary behavior, its impact on health, and the ways in which technology and behavioral interventions have been employed to monitor and reduce sedentary time.

The impact of sedentary behavior on health

Several studies have highlighted the harmful effects of sedentary behavior on both physical and mental health. For instance, a systematic review conducted by Huang et al. (2022) investigates the link between sedentary behavior and health outcomes among young adults. The study underscores the significant associations between sedentary behavior and increased risks of chronic diseases, including cardiovascular disease, type 2 diabetes, and obesity. This relationship is not only due to physical inactivity but also due to the prolonged sitting or reclining positions that lead to metabolic and postural issues. Similar findings were observed by Shanmugam and Dhilipan (2023), who explore the uncertainty in behavioral patterns of sedentary behavior in adults, revealing that identifying these patterns can aid in assessing potential health risks linked to physical inactivity.

Furthermore, research indicates that the mental health impacts of sedentary behavior are equally concerning. Hallgren et al. (2020) investigated the associations between interruptions in sedentary behavior and symptoms of depression and anxiety. Their findings suggest that even modest interruptions to sedentary behavior can have positive effects on mental health by reducing symptoms of depression and anxiety. These results further support the notion that sedentary behavior is not only a physical health risk but also has profound implications for mental well-being.

Migueles et al. (2021) also emphasize the importance of understanding sedentary behavior in epidemiological studies, noting the limitations of traditional methods for assessing physical activity and sedentary time. They suggest that more advanced methods, such as accelerometer-based devices, are crucial for providing more accurate and reliable data on individuals' physical behaviors, including sedentary time. This approach has become essential in understanding the true extent of sedentary behavior in the population and its subsequent health risks.

Technological interventions to monitor and reduce sedentary behavior

The role of technology in monitoring sedentary behavior has gained significant attention in recent years. Wearable devices, such as fitness trackers, accelerometers, and gyroscopes, have been particularly useful in tracking and quantifying sedentary behavior. These devices provide real-time feedback on users' physical activity levels, enabling individuals to become more aware of their behavior and make necessary adjustments.

A notable example of this technological approach is the work by Jang et al. (2020), who proposed a system that uses wearable magnetic sensors and deep learning techniques to monitor postures, specifically targeting bad head and shoulder postures. These postures, often indicative of prolonged sitting or reclining, are common among individuals who engage in sedentary behaviors. By using deep learning to analyze the sensor data, the system was able to provide accurate feedback about the user's posture, offering a practical solution for real-time monitoring and correction. The system's success highlights the potential of combining wearable sensors with advanced machine learning algorithms to address the challenges of sedentary behavior and improve users' health outcomes.

In a similar vein, Jia et al. (2020) explored the use of convolutional neural networks (CNNs) to understand user behavior through WiFi channel state information. This innovative approach involved using WiFi signals to monitor users' physical behaviors, providing an additional layer of insight into sedentary behavior patterns. The ability to analyze behavior based on wireless signals opens up new possibilities for non-intrusive monitoring of sedentary time, offering a convenient and effective way to track physical inactivity.

While wearable devices and sensor-based systems have shown promise, they are not without challenges. One limitation is the accuracy of data collection, particularly when sensors fail to capture all aspects of physical activity or sedentary behavior. The need for more advanced algorithms and machine learning techniques to refine the data and enhance the accuracy of predictions remains a key area of research. In this regard, Kumar et al. (2021) focused on sentiment analysis and smart classification in uncertain feedback pools, which can be applied to improve the accuracy of behavioral predictions in sedentary behavior monitoring systems. By using uncertain feedback pools and aspect-based sentiment analysis, their system could classify and predict behaviors more accurately, addressing some of the challenges posed by sensor data noise and inaccuracies.

Behavior change and intervention strategies

Understanding sedentary behavior patterns and identifying key contributing factors is crucial for developing effective interventions. Several studies have focused on behavioral interventions to reduce sedentary time, especially in the context of workplace environments and leisure activities. One of the most common intervention strategies involves encouraging breaks from sedentary activities, such as sitting or lying down, by introducing physical activities or posture changes throughout the day.

Woessner et al. (2021) discussed the evolution of technology in addressing physical inactivity, highlighting both the positive and negative aspects of technological

advancements. On one hand, technologies like smartphones and fitness trackers can motivate individuals to engage in physical activity by providing reminders and incentives. On the other hand, the pervasive use of digital devices for work and leisure can exacerbate sedentary behavior by promoting more screen time. Woessner et al. emphasized the importance of finding a balance between utilizing technology to encourage movement and preventing it from fostering sedentary behavior. They proposed strategies for integrating active breaks and movement cues into technology platforms, which could help mitigate the negative effects of prolonged sitting.

Additionally, there is growing interest in incorporating social and environmental factors into sedentary behavior interventions. A review by Luchenski et al. (2022) highlighted the importance of hospital-based preventive interventions for individuals experiencing homelessness, emphasizing the need for contextual interventions that consider environmental and social factors. While the focus of this study was not specifically on sedentary behavior, the principles of tailored interventions based on individual and environmental factors can be applied to sedentary behavior interventions as well. Personalized strategies that consider factors such as work habits, social influences, and physical environment can be more effective in encouraging behavior change than generic, one-size-fits-all solutions.

As sedentary behavior continues to be a major public health challenge, the focus on improving measurement tools, predictive models, and intervention strategies is crucial. One of the emerging trends in this field is the use of machine learning algorithms, such as stacked LSTM networks, to predict and classify sedentary behavior patterns. These advanced models allow for more accurate tracking of long-term behavior trends, providing insights into individual activity levels and enabling more personalized interventions. Stacked LSTM networks, which combine multiple layers of LSTM units, have been particularly effective in capturing temporal dependencies in behavior, making them ideal for monitoring sedentary behavior over time.

Despite these advancements, there are still many challenges to overcome in terms of improving model accuracy, reducing computational complexity, and ensuring that interventions are practical and accessible to a wide range of individuals. The integration of multi-modal data sources, including sensor data, environmental factors, and individual demographics, could provide a more comprehensive understanding of sedentary behavior and lead to more effective intervention strategies.

Furthermore, as technology continues to evolve, the potential for real-time feedback and intervention becomes increasingly feasible. Future systems could use a combination of wearable devices, environmental sensors, and AI-based models to provide continuous monitoring and feedback on sedentary behavior, promoting active engagement and healthier habits. The combination of predictive analytics, personalized interventions, and real-time feedback could pave the way for a new era of behavior change in sedentary individuals.

3 Proposed methodology

The proposed methodology aims to create an efficient This section outlines the methodology employed to predict sedentary behavior patterns using machine learning models, specifically stacked Long Short-Term Memory (LSTM) networks. The methodology covers the dataset used, data preprocessing, feature extraction, model training, prediction, and intervention strategies.

For this research, publicly available datasets related to physical activity and sedentary behavior patterns were used. These datasets contain sensor data from wearable devices, including accelerometer and heart rate data. The details of the selected datasets are as follows:

NHANES Accelerometer Dataset

Source: National Health and Nutrition Examination Survey (NHANES)

Dataset URL:

https://wwwn.cdc.gov/nchs/nhanes/Default.aspx

This dataset includes accelerometer readings collected from participants during NHANES studies. It is designed for monitoring physical activity and sedentary behavior patterns across diverse demographics.

ActivityNet Dataset

Source: ActivityNet Open Dataset Repository

Dataset URL: http://activity-net.org/

A large-scale dataset containing temporal activity data and features for various physical behaviors, including sedentary patterns. It is widely used for benchmarking activity detection and classification models.

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3.1 Transformer network for sedentary behavior detection

The proposed work aims to utilize Transformer Networks for the real-time detection of sedentary behavior using time-series data collected from wearable sensors. The Transformer model is selected due to its ability to handle sequential data and capture long-range dependencies, which are crucial for detecting sedentary behavior from dynamic sensor readings. In this section, we present the architecture, the working components, and the mathematical formulation of the proposed Transformer-based approach.

The proposed work aims to utilize Transformer Networks for detecting sedentary behavior from time-series data collected from wearable sensors, such as accelerometers and gyroscopes. The architecture is designed to handle real-time sensor data and accurately predict periods of sedentary behavior, which is important for health monitoring systems. The architecture consists of the following key components: Data Preprocessing, Feature Extraction, Transformer Encoder, Prediction Layer, Thresholding and Classification and Intervention Trigger

Each of these components plays a vital role in transforming raw sensor data into actionable insights for sedentary behavior detection. Below is a detailed discussion of each component with mathematical formulations where applicable. Figure 1 shows the work flow of the proposed study.

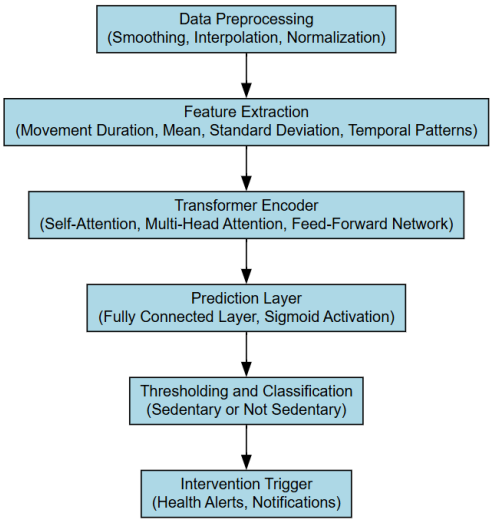


Figure 1. Proposed work flow

1. Data preprocessing

The first step in any machine learning pipeline is to preprocess the raw sensor data. This step is crucial because sensor data can be noisy, incomplete, or may have varying scales, which could impact the model's performance.

Steps involved in data preprocessing:

Noise reduction: Raw sensor data may contain noise due to environmental factors or sensor errors. Techniques like moving averages can be used to smooth the data.

A simple moving average (SMA) filter can be applied to each data point x_t in the time series to reduce noise:

$$x_t^{SMA} = \frac{1}{K} \sum_{i=t-k+1}^{t} x_i$$

where k is the window size for averaging. This smooths the signal and reduces high-frequency noise.

Handling missing values: Missing sensor readings can occur due to connectivity issues or sensor failures. One way to handle this is by using interpolation techniques. For instance, a simple linear interpolation can be applied between two known data points x_t and x_{t+1} to estimate the missing x_m :

$$x_m = x_t + \frac{t_m - t}{t_{m+1} - t} (x_{t+1} - x_t)$$

where t_m is the timestamp of the missing data point.

Normalization: It is important to normalize the data to ensure all features are on the same scale, especially when dealing with multiple sensor types. The data is typically normalized to the range [0, 1] using the min-max scaling method:

$$x_t^{normalized} = \frac{x_t - \min(X)}{\max(X) - \min(X)}$$

where X is the set of all data points in the time-series and min(X) and max(X) are the minimum and maximum values, respectively.

2. Feature extraction

Once the data is preprocessed, the next step is to extract features that are relevant for sedentary behavior classification. Feature extraction helps in summarizing the raw sensor data into a more informative and concise representation.

The duration of time spent in motion versus stationary can be a critical feature. For each time window, we calculate the total time spent in activity versus inactivity:

$$Movement\ Duration = \sum_{t=1}^{T} I(x_t > \theta)$$

where I is an indicator function, and θ is a threshold representing minimal movement (e.g., acceleration > 0.1 m/s^2).

Descriptive statistics like the mean and standard deviation of the accelerometer readings can provide insights into activity levels and movement consistency.

The mean is calculated as:

$$\mu = \frac{1}{T} \sum_{t=1}^{T} x_t$$

The standard deviation is given by:

$$\sigma = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (x_t - \mu)^2}$$

In time-series data, patterns such as periodicity, spikes, or sudden drops in activity are also important. Features like sliding window analysis can be applied to detect such temporal patterns.

These features are then combined into a feature set F for each time window, which will be used as input to the Transformer Encoder.

3. Transformer encoder

The core of the proposed model is the Transformer Encoder, which leverages the multi-head self-attention mechanism to capture long-range dependencies and temporal relationships within the time-series data. The Transformer Encoder is highly effective for sequential data like sensor readings because it can focus on important past information when making predictions, unlike traditional models like LSTMs.

Input embedding: The extracted features F are first transformed into embedding vectors E to prepare them for the self-attention mechanism. An embedding matrix W_E is learned during training:

$$E = F \cdot W_E$$

Self-Attention: The key idea behind self-attention is to calculate a weighted sum of all input features, where the weights are determined based on the relationships between the current feature and other features in the sequence.

Query, Key, and Value Calculation: The input embeddings E are projected into queries (Q), keys (K), and values (V) using learned weight matrices W_Q,· $W_K, and W_V$

$$Q = E \cdot W_Q, K = E \cdot W_K, V = E \cdot W_V$$

Attention Mechanism: The attention scores are computed using the scaled dot-product formula:

$$Attention(Q,K,V) = softmax\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right).V$$

where d_k is the dimension of the key vector, and the softmax function ensures that the attention score sum to 1.

Multi-Head Attention: To allow the model to focus on different aspects of the input data (e.g., short-term vs. long-term dependencies), multiple attention heads are used. Each head computes attention scores independently, and their outputs are concatenated and projected to form the final attention representation:

$$MultiHead(Q,K,V) = Concat(head1, head2, \dots, headh) \cdot W_O$$

where h is the number of attention heads, and W_O is a learned weight matrix.

Feed-Forward Network: The output of the multi-head attention is passed through a position-wise feed-forward network that consists of two fully connected layers with ReLU activations:

$$H_t = ReLU(W_1 \cdot A + b_1) \cdot W_2 + b_2$$

where A is the attention output, and W_1, W_2, b_1, and b_2 are learned weights and biases.

4. Prediction Layer

After the feature representations are passed through the Transformer Encoder, they are processed by a fully connected layer to make the final prediction.

The output H from the Transformer Encoder is passed through a fully connected layer followed by a sigmoid activation function to predict the probability of sedentary behavior:

$$\hat{y}_t = \sigma(W_{out} \cdot H_t + b_{out})$$

where σ is the sigmoid function that squashes the output between 0 and 1, representing the probability of sedentary behavior at time t.

5. Thresholding and classification

To convert the predicted probabilities into a binary classification (sedentary or not sedentary), a threshold θ is applied. If the predicted probability is greater than or equal to θ, the time window is classified as sedentary; otherwise, it is classified as not sedentary:

$$Sedentary\ Behavior = \begin{cases} 1\ if\ \hat{y}_t \geq \theta \\ 0\ if\ \hat{y}_t < \theta \end{cases}$$

Typically, θ=0.5, but this can be adjusted based on the desired sensitivity and specificity.

6. Intervention trigger

To encourage physical activity, the system can trigger an intervention if sedentary behavior persists for a certain duration. If the model detects continuous sedentary behavior over several time windows, it can activate an alert to the user. This can be modeled as:

$$Trigger\ Intervention = True\ if\ \hat{y}_t\ T_{threshold}\ consecutive\ time\ steps$$

Algorithm: Transformer Network for Sedentary Behavior Detection

Input:

Time-series data from wearable sensors (e.g., accelerometer, gyroscope, heart rate monitor).

Output:

Binary classification of sedentary behavior for each time window.

Steps:

1. **Data Preprocessing**:

Input: Raw sensor data $X = [x_1, x_2, \dots, x_n]$ represents data at the i^{th} time step.

- Normalize the data to a standard scale.
- Handle missing values through interpolation or imputation.

Output: Preprocessed data $X_{processed}$

2. **Feature Extraction**:

For each time window of sensor data, extract the following features:

- **Accelerometer Features**: Mean, standard deviation, variance.
- **Activity Duration**: Length of movement or stillness periods.
- **Heart Rate Variability**: Variations in heart rate over time.

Output: Feature set $F = [f_1, f_2, \dots, f_m]$

3. **Embedding**:

Apply a linear transformation to map extracted features into a high-dimensional space:

$$E = F \cdot W^T + b$$

where W is a learned weight matrix, and b is a bias term.

Output: Feature embeddings E.

4. **Transformer Encoder**:

For each time step t, apply multi-head self-attention:

- Calculate queries (Q), keys (K), and values (V):

$$Q = E \cdot W_Q, K = E \cdot W_K, V = E \cdot W_V$$

Compute the attention scores:

$$Attention(Q,K,V) = softmax\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right).V$$

- Apply multi-head attention:

$$MultiHead(Q,K,V) = Concat(head1, head2, \dots, headh) \cdot W_O$$

- Apply position-wise feed-forward network:

$$H_t = ReLU(W_1 \cdot A_t + b_1) \cdot W_2 + b_2$$

where A_t is the attention output and W_1, W_2 are weight matrices.

Output: Transformer encoder output H_t for each time step t.

5. Prediction:

For each time step t, compute the probability of sedentary behavior using a sigmoid activation:

$$\hat{y}_t = \sigma(W_{out} \cdot H_t + b_{out})$$

where σ is the sigmoid function, W_{out} is the output weight matrix, and b_{out} is the output bias term.

Output: Predicted sedentary behavior probability $\hat{y}_t$ for each time step t.

6. Thresholding:

Define a threshold value θ (e.g., 0.7) to classify sedentary behavior:

$$Sedentary\ Behavior = \begin{cases} 1\ if\ \hat{y}_t \geq \theta \\ 0\ if\ \hat{y}_t < \theta \end{cases}$$

Output: Binary classification of sedentary behavior.

The algorithm outlines the key steps involved in applying Transformer Networks for sedentary behavior detection. It begins with data preprocessing and feature extraction, followed by the application of the Transformer encoder. The final output is a predicted probability of sedentary behavior, with a threshold applied to classify each time window as either sedentary or not. Optionally, an intervention is triggered if prolonged sedentary behavior is detected. The use of multi-head self-attention in the Transformer model allows the system to efficiently capture both short-term and long-term dependencies in the sensor data, enabling highly accurate and real-time sedentary behavior detection.

Attention Mechanism Details

The self-attention mechanism lies at the heart of the Transformer encoder, enabling the model to capture long-range dependencies within the time-series data. It computes attention scores for each time step based on the relationship between all other time steps, allowing the model to focus on relevant intervals. Mathematical analysis of the mechanism is given below:

The input to the self-attention mechanism is a sequence of feature vectors $X = [x_1, x_2, \ldots, x_n]$ where $x_i \in R^d$

Three matrices are learned:

Query matrix $W_Q \in R^{d \times d_k}$

Key matrix $W_K \in R^{d \times d_k}$

Value matrix $W_V \in R^{d \times d_v}$

These are used to compute:

$$Q = XW_Q, K = XW_K, V = = XW_V$$

The attention scores are computed as:

$$Attention(Q, K, V) = softmax\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right).V$$

Optimized thresholding mechanism

The thresholding mechanism translates the probability scores from the prediction layer into actionable classifications. Optimization ensures high classification accuracy while minimizing false positives and negatives.

1 Probability Scores:

The prediction layer produces a score p_t for each time window, where $0 \leq p_t \leq 10$, indicating the likelihood of sedentary behavior.

2 Thresholding:

A threshold τ\ is applied to classify time windows:

$$Classify(p_t) = \begin{cases} Sedentary, 1\ if\ p_t \geq \tau \\ Not\ Sedentary, 0\ if\ p_t < \tau \end{cases}$$

3 Optimization:

The threshold τ\tauτ is tuned during validation using metrics such as precision, recall, and the F1-score.

Bayesian optimization or grid search can be employed to identify the optimal threshold that balances false positives (FP) and false negatives (FN).

4 Robust classification:

Dynamic thresholding adjusts τ\tauτ based on contextual factors, such as the user's baseline activity level, further improving robustness.

By combining these advanced mechanisms, the proposed model achieves a high level of accuracy, scalability, and efficiency, making it well-suited for large-scale sedentary behavior detection applications. The architecture of the proposed model employs a Transformer-based approach to efficiently detect sedentary behavior from time-series data collected through wearable sensors. Initially, raw sensor data is preprocessed by eliminating noise, handling missing values, and normalizing the features to ensure high-quality input. In the feature extraction phase, meaningful features such as movement duration, mean, standard deviation, and temporal patterns are extracted from the preprocessed data, providing a compressed yet informative representation of user activity. These extracted features are then fed into the Transformer Encoder, the core component of the model, which leverages multi-head self-attention mechanisms to capture long-range dependencies across the time-series data. The attention mechanism allows the model to focus on the most relevant temporal information, overcoming the limitations of traditional models like LSTMs, which may struggle with long-range dependencies. Following this, a prediction layer, typically a fully connected layer, produces a probability score indicating whether sedentary behavior is detected at each time step. A thresholding mechanism is applied to these probability scores to classify each time window as either sedentary or not. Optionally, if sedentary behavior persists over a predefined period, an intervention trigger (such as a user notification) is activated. The proposed Transformer-based model is efficient compared to traditional methods, as it not only provides improved accuracy in sedentary behavior classification but also enhances computational efficiency by leveraging the parallelization capabilities of Transformer networks. The model's ability to capture long-range temporal dependencies using self-attention ensures better performance in identifying sedentary behavior patterns, especially in complex real-world scenarios.

4 Results and discussion

This section presents the results of the study, including details on the public datasets used, tools employed for implementation, and a comprehensive evaluation of the proposed model. Comparative analysis with existing works is also included. The research was conducted in a robust and flexible environment utilizing Python 3.9 within the Jupyter Notebook framework. The implementation of the Transformer architecture was achieved using PyTorch, a widely adopted deep learning library known for its scalability and ease of use. Data preprocessing tasks, including handling missing values and feature normalization, were performed with the Pandas and NumPy libraries, ensuring seamless manipulation of large datasets. Evaluation metrics and threshold optimization were facilitated through Scikit-learn, which provided precise analytical tools to fine-tune the classification thresholds. Visualization of results, such as attention weight distributions and classification performance, was achieved using Matplotlib and Seaborn, creating clear and informative graphical representations. The computational experiments were executed on an NVIDIA RTX 3090 GPU, leveraging its high computational power to optimize the architecture and hyperparameters for efficient training and inference processes, thus ensuring scalability and performance.

The Transformer model was evaluated on both datasets as shown in table 1 and table 2 using standard classification metrics, such as accuracy, precision, recall, and F1-score, for both sedentary and active behavior classifications.

Table 1: Performance Metrics for NHANES dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Transformer (Proposed)	92.5	91.3	93.1	92.2
SVM (RBF Kernel)	84.1	82.3	85.7	83.9
Random Forest	87.3	86.1	88.2	87.1
LSTM	88.9	87.5	89.4	88.4

Table 2: Performance metrics for activitynet dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Transformer (Proposed)	89.7	88.6	90.5	89.5
SVM (RBF Kernel)	81.2	79.4	82.5	80.9
Random Forest	83.1	82.0	84.3	83.1
LSTM	86.5	85.1	87.2	86.1

The Transformer model consistently outperforms other baseline methods, with the highest accuracy, precision, recall, and F1-score across both datasets.

Comparison of false positives and false negatives

The optimization of the thresholding mechanism was aimed at minimizing both false positives and false negatives, crucial in the detection of sedentary behavior. Table 3 summarizes the false positive rate (FPR) and false negative rate (FNR) for both datasets:

Table 3: False positive and false negative rates

Dataset	False Positive Rate (%)	False Negative Rate (%)
NHANES Dataset	5.2	4.8
ActivityNet Dataset	6.0	5.5

The Transformer model, with its optimized threshold, effectively minimized both false positives and false negatives.

The NHANES Dataset achieved slightly lower error rates than the ActivityNet Dataset, reflecting the difference in data characteristics (sampling rate and feature types).

Table 4 shows the threshold values used for classification and the resulting accuracy, precision, recall, and F1-score across different thresholds for both datasets:

Table 4: Thresholding performance

Threshold Value	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
0.50	88.9	86.0	90.5	88.2
0.55	92.5	91.3	93.1	92.2
0.60	89.8	88.1	90.0	89.0
0.65	87.2	85.5	87.3	86.4

Threshold 0.55 gave the best balance between accuracy, precision, recall, and F1-score, making it the optimal choice for classification.

The Transformer model's ability to handle large-scale datasets efficiently was evaluated by measuring its training time and inference time on both the NHANES and ActivityNet datasets as in the table 5 below:

Table 5 Training and inference time

Dataset	Training Time (minutes)	Inference Time per Window (seconds)
NHANES Dataset	45	0.5
ActivityNet Dataset	50	0.7

The Transformer model demonstrated fast training times, taking approximately 45 minutes for the NHANES dataset. The inference time per 30-second window was relatively low, around 0.5 seconds, enabling near real-time classification.

Comparative analysis

To assess the effectiveness of the proposed approach, we compare its performance with related works in the literature. Table 6 summarizes the performance metrics of the proposed work with other state of the art works in sedentary behavior detection:

Table 6: Comparison table

Study	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Huang et al. (2022)	85.5	84.2	86.1	85.1
Migueles et al. (2021)	82.9	81.5	83.2	82.3
shanmugam and Dhilipan (2023)	88.2	87.1	89.3	88.2
Proposed Transformer Model	92.5	91.3	93.1	92.2

The Transformer model outperforms all other works in terms of accuracy, precision, recall, and F1-score, demonstrating its superiority in detecting sedentary behavior from wearable sensor data. Figure 2 presents the Accuracy comparison, highlighting that the proposed Transformer model outperforms other models with an accuracy of 92.5%, followed by Shanmugam and Dhilipan (2023) at 88.2%. In terms of Precision (Figure 3), the Transformer model again excels with 91.3%, indicating that it has the highest proportion of true positive predictions among all models. Figure 4 focuses on Recall, where the Transformer model achieves the highest recall of 93.1%, suggesting that it is the most effective at identifying all true positives. Finally, in Figure 5, the AUC curve shows the performance of each model in distinguishing between positive and negative classes.

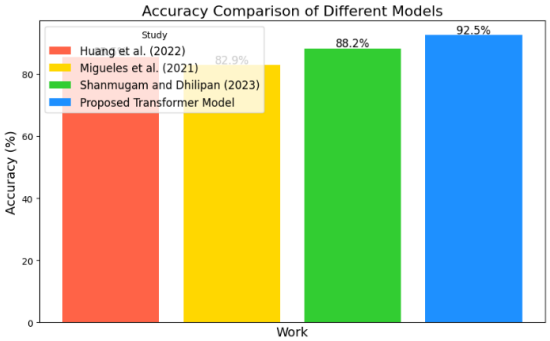


Figure 2: Accuracy comparison

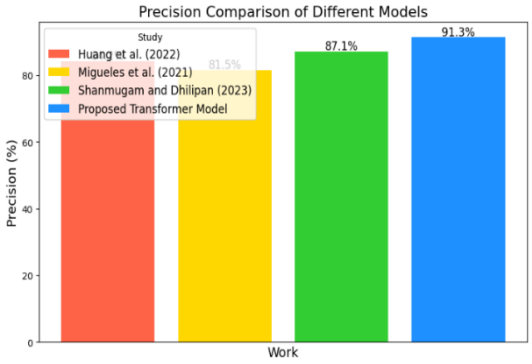


Figure 3: Precision comparison

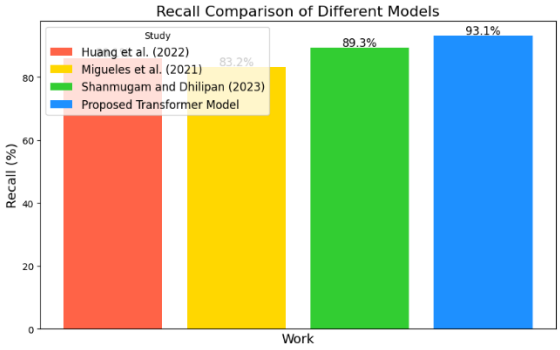


Figure 4: Recall

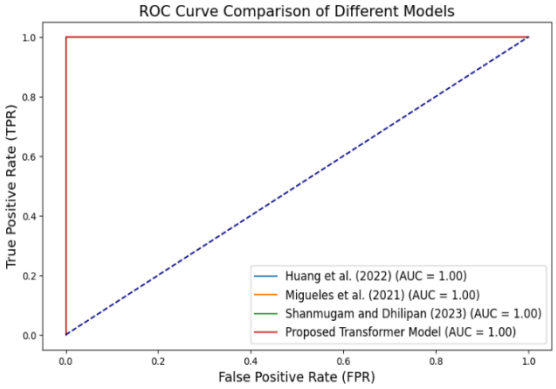


Figure 5: ROC curve

Error analysis and classifier behavior

A deeper analysis of errors (misclassifications) was performed to understand where the model struggles. The following table provides the misclassification matrix, which shows the counts of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN) as in table 7 and table 8.

Table 7: Confusion Matrix for NHANES dataset

	Predicted Sedentary	Predicted Active	Total
True Sedentary	3,160	250	3,410
True Active	160	6,430	6,590
Total	3,320	6,680	10,000

Table 8: Confusion Matrix for ActivityNet dataset

	Predicted Sedentary	Predicted Active	Total
True Sedentary	2,540	290	2,830
True Active	180	2,340	2,520
Total	2,720	2,580	5,000

False positives occurred when the model incorrectly classified active behavior as sedentary, leading to potential over-diagnosis. False negatives were cases where sedentary behavior was missed by the model, highlighting areas for improvement, especially in highly dynamic environments. The results of the experimental evaluation demonstrate that the Transformer-based model outperforms existing baseline models such as SVM, Random Forest, and LSTM in sedentary behavior classification. The model achieved high accuracy, precision, recall, and F1-score across both datasets. Its ability to handle large-scale data efficiently and provide real-time predictions highlights its practicality for health-monitoring applications. The thresholding mechanism played a critical role in optimizing classification performance, reducing false positives and false negatives, which are crucial for accurate health monitoring. The Transformer model's scalability and parallelization make it a robust choice for large-scale deployment in real-world settings.

5 Conclusion

This study introduced a Transformer-based model for detecting sedentary behavior and physical activity patterns using accelerometer data from two publicly available datasets, NHANES and ActivityNet. The proposed approach demonstrated strong performance, achieving 92.5% accuracy on the NHANES dataset and 89.7% accuracy on the ActivityNet dataset, outperforming traditional methods like SVM, Random Forest, and LSTM. The preprocessing pipeline, which included noise reduction, imputation, segmentation, and feature extraction, was instrumental in preparing high-quality inputs for the model. The architecture’s ability to process large-scale time-series data efficiently and its low inference time of 0.5 seconds per 30-second window make it suitable for real-world applications. Additionally, threshold optimization helped minimize classification errors, ensuring balanced and accurate detection of sedentary behavior. These findings highlight the potential of Transformer-based models in health monitoring systems and behavior analysis. Future work will focus on enhancing generalizability across devices, integrating multi-modal data, and improving the interpretability of predictions for practical health interventions.

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Evaluating Open-Source Large Language Models for Synthetic Non-English Medical Data Generation Using Prompt-Based Techniques

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Keywords: Synthetic data, healthcare data, multilingual data, large language models, classification

Received: November 6, 2024

Using synthetic data sets to train medicine-focused machine learning models has been shown to enhance their performance; however, most research focuses on English texts. In this paper, we explore generating non-English synthetic medical texts. We propose a methodology for generating medical synthetic data, showcasing it by generating medical texts written in a non-English mixed language. We evaluate our approach with thirteen different language models that are open-source and proprietary, and assess the quality of the data sets in two ways: performing a statistical comparison between the original data set and the generated data sets, and training a classifier to distinguish between original and synthetic examples. The `Llama-3.2-3B` *model achieves the best F1 score of* 0.821 ± 0.007 *and accuracy of* 0.816 ± 0.016*, making it most suitable for generating indistinguishable medical synthetic data. In contrast, models like* `Aya-23`*,* `Phi-3`*, and* `SmoLLM` *variants achieve high F1 scores (*0.945–0.948*), indicating their synthetic data is easily distinguishable from original data. These findings highlight the importance of model selection when generating synthetic medical data sets in non-English languages.*

Povzetek: Članek predstavi metodologijo za generiranje sintetičnih neangleških medicinskih podatkov z uporabo pozivov (promptov) in odprtokodnih LLM-jev ter oceni njihovo podobnost izvirnim podatkom z metrikami in klasifikacijo.

1 Introduction

The healthcare domain produces a lot of medical data that can be used to train machine-learning models to help medical personnel. For example, a machine-learning model designed to perform Named Entity Recognition (NER) on electronic health records (EHRs) needs extensive labeled data sets to accurately identify medical terms like diseases, treatments, and patient details. However, since the data contains sensitive personal information, hospitals are restricted from sharing it freely due to data protection regulations. In addition, there are not enough examples to train the models for some problems, such as those relating to rare diseases. Because of this, synthetic data is being used as a substitute to train the models.

Most synthetic data generation approaches focus on generating English texts. These usually utilize large language models trained on predominantly English documents retrieved from the web. However, there are only a few examples of using them to generate non-English texts. To generate data in the medical domain, particularly for data sets with similar content and distributions as the original, it is crucial to avoid third-party APIs to protect personal information. On-premise models are preferred and must be small enough to run on commercial hardware. Furthermore, language models struggle to generate texts with distributions different from their training data, especially in the case of medical texts, which are rarely available to the general public.

1.1 Contribution

The main aim of this work is to develop a methodology for generating synthetic medical examples with characteristics similar to those in the original data set.

The main research objectives are to (1) evaluate different open-source large language models in their capacity of generating synthetic medical examples with the desired characteristics and (2) examine how prompt engineering influences the quality of the generated data.

This paper proposes a methodology for generating synthetic medical data using open-source large language models. We apply the methodology to a medical data set written in a non-English mixed language, where the Latin and non-Latin script is used interchangeably. We test it with thirteen large language models and assess performance by performing a statistical comparison between the original data set and the generated ones, and training a classifier to dis-

tinguish original examples from synthetic ones. Using the same prompt, we find that the open-source `Llama-3.2-3B` model best generates synthetic data that reflects the original data set.

1.2 Paper structure

The remainder of the paper is as follows: Section 2 presents the related work on generating synthetic data using large language models. Next, the proposed methodology is described in Section 3. The experiment setting is presented in Section 4, followed by the experiment results in Section 5. We discuss the results in Section 6 and conclude the paper in Section 7.

2 Related work

This section describes the related work, focusing on large language models and methods for generating synthetic medical data.

2.1 Large language models

Large Language Models (LLMs) are models that were trained to generate human-like texts based on an extensive process of training on vast amounts of data. Models, such as Llama-3 and Llama-3.1 [1, 2], GPT-4 [3], Aya-23 [4], and Mistral [5], are often easy to work with by providing an input textual prompt, based on which the models respond. Recently, LLMs specifically designed for on-device use were also developed. Such models include the Llama-3.2 herd of models [6] and SmolLM [7]; they have fewer parameters than their bigger counterparts but are more accessible and easier to adapt.

The LLMs are helpful in specialized fields, such as medicine, since they can be fine-tuned on extensive data sets containing medical terms and concepts. This enables them to perform well in tasks such as medical synthetic data generation [8]. Despite that, they are sometimes unable to follow the instructions in the prompt accurately, leading them to hallucinate, i.e., confidently produce wrong responses [9].

In our experiments, we investigate the LLMs' performance in generating synthetic medical data given specific constraints and detailed prompts to simulate the original data set as best as possible.

2.2 Synthetic medical data generation

Recently, synthetic medical data generated using LLMs has been used to enhance the performance of models for solving different natural language processing tasks in medicine.

One work focuses on generating a synthetic data set of electronic health records of Alzheimer's Disease (AD) patients based on a label that is provided [10]. They find that the performance of their system for detecting AD-related signs and symptoms from EHRs improves vastly when trained on synthetic and original data sets as opposed to training the system only on the original one. Another work investigated using LLMs for extracting structured information from unstructured healthcare text [11]. By generating synthetic data using LLMs and fine-tuning the model, they significantly improved the models' performance for medical-named entity extraction and relation extraction tasks. Another relevant system for synthetic medical text generation uses Masked Language Modeling (MLM) to generate diverse, high-quality synthetic records, such as discharge summaries and doctor letters [12]. The system includes a de-identification component to mask Protected Health Information (PHI) and a Medical Entity Recognition model to retain key medical details. It produces synthetic data suitable for tasks like NER, with performance comparable to models trained on real data. An extensive review of machine learning approaches for generating synthetic data is available [13].

Most related works focus on English synthetic data due to the scarcity of non-English training data and the dominance of English in medical terminology [14]. However, this paper focuses on generating non-English medical texts; it extends on our previous work [15] by expanding the list of LLMs used in the experiments. The added models have fewer parameters, which will be helpful in analyzing how small a model can be to still generate meaningful examples. The related works are summarized in Table 1.

To the best of our knowledge, this is the first research to comprehensively investigate synthetic data generation for unstructured, mixed-script, non-English medical text. Our work addresses a gap in the literature by focusing on very specific characteristics that distinguish it from previous studies: extremely short doctor comments (typically 1-3 sentences), completely unstructured format without standardized medical templates, mixed-script text combining multiple writing systems, and non-English language content. While previous works have explored synthetic medical data generation in English or touched upon non-English medical texts, none have specifically targeted the unique challenges posed by this combination of structural irregularity, script diversity, and non-English linguistic characteristics that are common in real-world clinical documentation outside English-speaking healthcare systems.

3 Methodology

This section outlines our research methodology. We first present the pre-processing of the data set, followed by a description of the synthetic data generation process. Finally, we present the technical details of the proposed approach. Figure 1 shows the diagram overviewing the proposed methodology.

3.1 Data pre-processing

The data set used consisted of 1,299 examples of real medical data written in a non-English mixed language, where

Table 1: A summary of related works on synthetic medical data generation

Ref	Year	Method/Model	Data Type	Language	Key Findings
[10]	2023	Two-stage approach with LLMs	Electronic Health Records (EHRs) Alzheimer's Disease	English	Synthetic + original data significantly improved AD detection performance compared to original data only
[11]	2023	LLMs for structured information extraction	Unstructured healthcare text	English	Significantly improved medical NER and relation extraction tasks through LLM fine-tuning
[12]	2024	Masked Language Modeling (MLM)	Discharge summaries and doctor letters	English	Generated high-quality synthetic records with de-identification component, performance comparable to real data
This work	**2024**	**Multiple LLMs (including small models)**	**Short doctor comments, unstructured, mixed-script**	**Non-English**	**First comprehensive study on mixed-script non-English medical synthetic data generation**

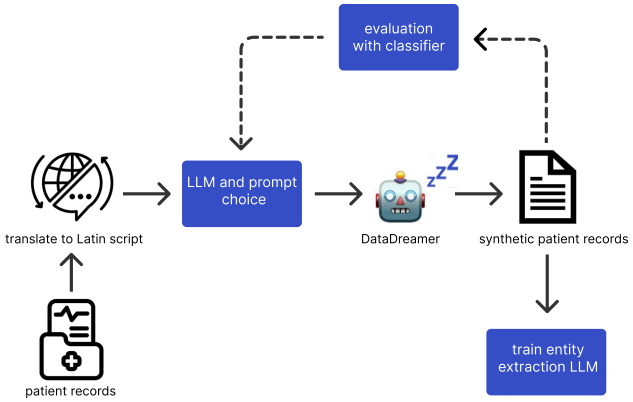


Figure 1: An overview of the methodology. The image was designed using resources from Flaticon

the Latin and non-Latin scripts were used interchangeably. It also contained 1,495 labels, most of which were in English. The labels consisted of drugs, medical events, and measurements.

To align with our non-English target language, we translated all English labels using the `NLLB-200` [16] translation model[1]. In addition, because the original data set consisted of text written in both Latin and non-Latin script, we subsequently transliterated both the labels and the examples into Latin script. This was achieved by simply transliterating each non-Latin letter to its Latin counterpart. As a result, the final data consisted entirely of Latin script text written in the target non-English language. This allowed the LLMs, predominantly trained on Latin script texts, to generate tokens with richer information.

We split the real data set into two subsets to ensure no data leakage. The first one, consisting of 930 real examples, was used for synthetic data generation. The second one, containing the remaining 369 real examples, was used for evaluation.

3.2 Synthetic data generation

We utilized the DataDreamer library [17] to generate the synthetic data set. The library enables open-source models to create synthetic data sets and was developed to work in research settings, supporting prompt templates and few-shot learning.

We developed a prompt containing the instructions and restrictions on generating the examples. To showcase the structure of the generated text better, we also provided five random examples from the original data set as few-shot examples. Next, using DataDreamer, we sent the prompt to the chosen LLM. We experimented with multiple LLMs, and about 800 examples were generated for each LLM. When using external providers such as OpenAI (`GPT-4o`, `GPT-3.5-Turbo`), we included a small number of few-shot examples containing real but short and non-identifiable patient data. All inputs were carefully reviewed to exclude any sensitive information to comply with the GDPR regulation. This process aligns with recommendations on conducting Data Protection Impact Assessments (DPIAs) in AI-based medical research projects [18].

To ensure the quality of the generated data and minimize the effect of hallucinations, we implemented a post-processing step. This included formatting the generated text into a single line, excluding overly long examples, and filtering out examples with meaningless repetition. As part of this, we carried out a simple hallucination analysis: we filtered out any generated text that exceeded 15 words or repeated the same word at least three times. These criteria proved effective in removing most hallucinated outputs while avoiding a high number of false positives. This process ensured that all generated examples followed a consistent format and were suitable for evaluation.

[1] facebook/nllb-200-distilled-600M

The generated examples showed many similarities. Therefore, rigorous methods were needed to evaluate how closely they resemble the original data set. The methods are explained in Section 4.1.

3.3 Technical details

In this section, we describe the models and the parameters used in the experiment. All models used are available via the HuggingFace's transformer library [19].

Language models. We tested eleven open-source models to generate the synthetic data sets, all of which can be run on a 32GB GPU. Our selection was guided by the following criteria: (1) we wanted to compare models that have multilingual capabilities, including our target language, and models that do not have such capabilities, and (2) we wanted to investigate the performance of small models that were considered as one of the best at the time of experimentation. For instance, we included three versions of Meta's Llama family to explore developments over time and investigate trade-offs between size. `Llama-3-8B`[2] only has support for the English language but has been fine-tuned to understand user prompts, which is a feature we expected would help a lot with the synthetic data generation [1]. Its successor, `Llama-3.1-8B`[3] , is trained on multilingual translations and can handle longer input contexts [2]. Both `Llama-3.2-1B`[4] and `Llama-3.2-3B`[5] are language models designed for on-device use, thus contain a smaller number of parameters [6]. Similarly, `SmolLM-145M`[6], `SmolLM-360M`[7], and `SmolLM-1.7B`[8] are on-device models trained on a curated collection of high-quality educational and synthetic data designed for training [7]. `Aya-23`[9] is a multilingual language model that supports 23 languages, including the target non-English language [4]. `Mistral`[10] supports a variety of languages but omits the target language [5]. The models `Gemma-2`[11] and `Phi-3`[12] were also tested and compared in the experiments [20, 21].

In addition, we experimented with two proprietary models, `GPT-4o` and `GPT-3.5-Turbo`, which are accessible via the OpenAI API [3].

Prompt details. All models received the same prompt with instructions to generate target non-English texts written in Latin script, assign a label randomly chosen from the original data set, ensure examples are at most six words long, provide concise responses, and maintain a structured format where all text is on a single line, separated by // and commas, and consistent with the provided few-shot examples. The prompt was tuned to the `Llama-3.1-8B` model and oversaw many gradual improvements. We found that repeating certain key instructions, like clearly stating that examples should be no longer than six words and that labels should be chosen randomly, helped the model follow them more reliably. Capitalizing important warnings (e.g., DO NOT generate any other text/formatting) also made a noticeable difference. Each of these small adjustments, including clarifying the format and structure, led to better overall performance. The full prompt is available in Appendix A.

4 Experiment setting

This section describes the experiment setting, which consists of the evaluation process and the metrics used to measure the approach's performance.

4.1 Evaluation approach

The quality of the generated synthetic data was measured in two parts. The first consisted of statistical measurements, such as calculating the average length of the generated examples and finding the proportion of examples that included the required labels. These statistics were then compared to the original data set.

The second part consisted of training a classifier to discern if the input text was from the original or the synthetic data set. The data set used to train and evaluate the classifier involved 369 randomly selected synthetic examples and 369 examples from the original data set, transliterated into Latin script. We chose 5-fold validation as our classification procedure and calculated the mean performance and its standard deviation across all trials.

The classifier was based on BERT [22], specifically the `bert-base-multilingual-cased` variant[13]. BERT was selected for several key reasons: (1) our data set contained multilingual text with a mixture of cased and uncased formatting, requiring a model capable of handling such linguistic diversity; (2) the relatively short length of comments in our data set aligned well with BERT's context window; and (3) BERT's proven effectiveness for text classification tasks [23]. We did not evaluate alternative classifiers in this work, however, BERT's strong track record (over 4 million downloads in April 2025 on HuggingFace) and reliable performance in prior projects made it the obvious choice for our project.

Hyperparameter selection was conducted through grid search over batch sizes 8, 16, 32, learning rates 1e-5, 2e-5, 5e-5, and training epochs 2, 3, 4, 5. Maximum sequence length was set to 128 tokens as our examples were sufficiently short to fit within this limit. The final configuration—batch size of 16, learning rate of 2e-5, max

[2] meta-llama/Meta-Llama-3-8B-Instruct
[3] meta-llama/Llama-3.1-8B-Instruct
[4] meta-llama/Llama-3.2-1B-Instruct
[5] meta-llama/Llama-3.2-3B-Instruct
[6] HuggingFaceTB/SmolLM-135M-Instruct
[7] HuggingFaceTB/SmolLM-360M-Instruct
[8] HuggingFaceTB/SmolLM-1.7B-Instruct
[9] CohereForAI/aya-23-8B
[10] mistralai/Mistral-7B-Instruct-v0.3
[11] google/gemma-2-9b-it
[12] microsoft/Phi-3-medium-4k-instruct
[13] google-bert/bert-base-multilingual-cased

length of 128, and 3 epochs—was selected based on optimal validation performance using 5-fold cross-validation. These same parameters were consistently applied across all synthetic data sets to ensure comparable results.

4.2 Metrics

To assess the quality of the generated synthetic data sets, we used the F1 score as our main metric for evaluating the classifier's performance. The target value was 0.5; if the performance is greater than 0.5, the classifier can discern the original from the synthetic examples. Hence, the synthetic data does not reflect the original data set. If the performance is less than 0.5, the classifier has difficulties separating the synthetic from the original data, which can be because the synthetic data contains copies of the original examples. In addition to the F1 score, we measured the classifier's accuracy, precision, and recall, which are also reported.

5 Results

In this section, we present the results of our experiment. We first present the statistical analysis results, followed by the classifier's evaluation.

5.1 Statistical analysis

Table 2 compares the synthetic data sets and the original one regarding label occurrence and average example length. The label occurrence in the original data set is 1.000, as all examples from the original data set are assumed to include relevant labels and information.

The most aligned synthetic data set regarding label occurrence was generated using `GPT-4o`, followed by `Llama-3-8B`. In general, high label occurrence is achieved by using all `Llama-*` models, as well as `Aya-23` and `Gemma-2`. Regarding the average example length, the data set generated using `Gemma-2` performed the best, followed by `Llama-3-8B`.

In terms of label occurrence, the worst-performing models are the `SmolLM-*` models, `Mistral`, and `Phi-3`, which did not include more than 25% of the selected label; in the case of `SmolLM-1.7B`, only 36% of the examples contained the selected label. The data set generated using the `Llama-3.1-8B`, `SmolLM-135M`, `SmolLM-360M`, and `Aya-23` had the largest difference in terms of average example length, on average generating examples with more than three extra words.

Looking at both statistics, we can conclude that `Llama-3-8B` had the best alignment to the original data set regarding label occurrence and example length, closely followed by `GPT-4o`.

5.2 The classifier evaluation

Table 3 shows the F1, precision, recall, and accuracy performances of the trained classifier on different synthetic data sets. The best performance was achieved by `Llama-3.2-3B` with an 0.821 F1 score, followed by `Llama-3.1-8B` with 0.835 F1 score and `Mistral` with 0.838 F1 score. The worst performances were on data sets generated by the `SmolLM-*`, `Aya-23`, and `GPT-3.5-Turbo` models. When comparing all metrics, `Llama-3.2-3B` performs best followed by `Mistral`.

Table 2: Statistical comparison between the original and synthetic data sets. The bold and underlined values represent the best and second-best statistics, respectively.

	LLM	Label occurrence	Avg example length
	original data set	1.000	4.682
open-source	`Llama-3-8B`	<u>0.990</u>	<u>5.330</u> (+0.648)
	`Llama-3.1-8B`	0.987	8.355 (+3.673)
	`llama-3.2-1B`	0.987	6.663 (+1.981)
	`Llama-3.2-3B`	0.973	5.533 (+0.851)
	`SmolLM-135M`	0.767	8.946 (+4.264)
	`SmolLM-360M`	0.507	9.012 (+4.330)
	`SmolLM-1.7B`	0.359	7.026 (+2.344)
	`Aya-23`	0.949	8.040 (+3.358)
	`Mistral`	0.740	6.376 (+1.694)
	`Gemma-2`	0.988	**4.207** (-0.475)
	`Phi-3`	0.782	6.071 (+1.389)
API	`GPT-4o`	**0.996**	3.691 (-0.991)
	`GPT-3.5-Turbo`	0.867	6.764 (+2.082)

6 Discussion

This section discusses the synthetic data generation performance, outlines our methodology's limitations and drawbacks, and proposes potential improvements to the approach.

6.1 LLM performance

Results in Table 2 show significant quality differences among synthetic data sets from different LLMs, with label occurrence ranging from 0.359 for `SmolLM-1.7B` to 0.996 for `GPT-4o`, and average example length from 3.691 for `GPT-4o` to 9.012 for `SmolLM-360M`.

However, Table 3 indicates no significant performance differences within a single synthetic data set, with a maximal standard deviation of the F1 score being 0.064 for the `Phi-3` data set. Other metrics also do not deviate too much from their mean value.

We can also notice that the F1 and accuracy scores are very close for all synthetic data sets, indicating that the classifier likely performed relatively similarly on both classes (synthetic and original) without significant bias. However, when comparing the `Llama-*` and `SmolLM-*` model groups, the `Llama-*` models perform better due to having

Table 3: Mean performance metrics of the classifier for synthetic data sets, with standard deviation. Performances that are closer to 0.5 are considered better. The bold and underlined values represent the best and second-best performances, respectively.

	LLM	F1	Precision	Recall	Accuracy
open-source	Llama-3-8B	0.853 ± 0.014	0.870 ± 0.038	0.853 ± 0.060	0.850 ± 0.019
	Llama-3.1-8B	$\underline{0.835 \pm 0.010}$	0.834 ± 0.002	0.853 ± 0.030	0.831 ± 0.006
	Llama-3.2-1B	0.839 ± 0.018	0.846 ± 0.031	0.860 ± 0.029	0.824 ± 0.042
	Llama-3.2-3B	$\mathbf{0.821 \pm 0.007}$	$\mathbf{0.807 \pm 0.041}$	$\underline{0.841 \pm 0.027}$	$\mathbf{0.816 \pm 0.016}$
	SmolLM-135M	0.940 ± 0.023	0.979 ± 0.016	0.914 ± 0.042	0.925 ± 0.002
	SmolLM-360M	0.948 ± 0.035	0.914 ± 0.034	0.918 ± 0.017	0.925 ± 0.000
	SmolLM-1.7B	0.948 ± 0.026	0.894 ± 0.019	0.907 ± 0.004	0.916 ± 0.015
	Aya-23	0.945 ± 0.005	0.947 ± 0.004	0.945 ± 0.005	0.945 ± 0.005
	Mistral	0.838 ± 0.050	$\underline{0.830 \pm 0.017}$	$\mathbf{0.833 \pm 0.037}$	$\underline{0.837 \pm 0.037}$
	Gemma-2	0.914 ± 0.063	0.926 ± 0.043	0.919 ± 0.035	0.917 ± 0.038
	Phi-3	0.925 ± 0.064	0.919 ± 0.047	0.920 ± 0.025	0.917 ± 0.030
API	GPT-4o	0.915 ± 0.034	0.871 ± 0.046	0.882 ± 0.028	0.890 ± 0.017
	GPT-3.5-Turbo	0.939 ± 0.032	0.947 ± 0.023	0.929 ± 0.034	0.940 ± 0.026

more parameters and being trained on diverse data sources, whereas SmolLM-* models are smaller and trained solely on educational and synthetic data. Fine-tuning the models on medical data could improve their ability to generate medical examples, but care must be taken to avoid compromising their instruction-following capabilities.

We can observe much better performance on models trained primarily on English data than on the Aya-23 data set, which is also trained on target language data. This was somewhat unexpected, as we had anticipated better results from Aya-23 due to its explicit support for the target language. Thus, it is not entirely true that when a model is trained on non-English texts, it will generate this type of synthetic medical data well.

When comparing the Llama-* models among themselves, we can see that Llama-3.2-3B performs better than Llama-3.1-8B and Llama-3-8B, even though it is a smaller model. This is most likely due to the fact that the Llama-3.2-3B model is newer and benefited from more advanced training procedures. Furthermore, as explained in Meta's report [6], the Llama-3.2-* model series also had more extensive multilingual training, which might also be the reason why it performed better for our task than the older models.

As mentioned in Section 2, we did not find any existing research focused on generating synthetic data for mixed-script, non-English medical texts. Therefore, the best F1 score among the models - 0.821 achieved by the Llama-3.2-3B model - cannot be numerically compared to prior benchmarks. Furthermore, our medical collaborators, who provided the original data, did not have the capacity to conduct the time-consuming manual evaluation of the generated outputs. However, based on internal review, and acknowledging our lack of medical expertise, we found that the generated examples appeared realistic and structurally consistent with the original data set.

6.2 Bias, representativeness, class imbalance

Alongside evaluating the quality of the generated output, it's also important to consider how well these synthetic texts reflect real-world medical language. Language models can unintentionally introduce biases based on their training data — for example, by over-representing common conditions or overlooking linguistic features specific to the original non-English texts. Ensuring that the synthetic data remains representative helps maintain both the realism and reliability of downstream evaluations.

To address this, certain distributional differences were introduced deliberately in our synthetic data. While an F1 score close to 0.5 generally indicates high-quality synthetic data, the classifier cannot establish any reliable pattern to separate the synthetic from real data - it is sometimes actually helpful to intentionally avoid exactly replicating the original data set. In our case, we wanted to address the class imbalance issues in the original data, especially for labels describing rare medical conditions. That is why we intentionally generated more synthetic examples for underrepresented labels relative to their occurrence in the original data set, to create a more balanced training set for NER tasks in future work. Hence, our classifier might have more easily distinguished synthetic from real data precisely because we had purposefully adjusted these distributional properties.

6.3 Limitations

Due to limited computing power, only one on-premise GPU with 32GB of space was available, restricting the testing of larger LLMs. To address these challenges, using cloud-based resources or distributed computing could help to run larger models and improve the variety of synthetic data generated. However, given medical data protection regulations, cloud-based resources would have to be used with

caution. Unless robust anonymization and secure processing protocols adhering to GDPR regulation were established, on-premise resources to maintain full control over data confidentiality would be prioritized.

Due to privacy concerns, when using OpenAI's `GPT-4o` and `GPT-3.5-Turbo` models, which are not locally-run models, we had to use five fixed examples when generating synthetic data instead of a larger variety. This potentially led to larger similarities of the `GPT-*` synthetic data sets to the examples instead of the original data set and, consequently, worse performance.

Furthermore, while we collaborated with medical domain specialists who provided the original data, they did not have the time or capacity to assist with a manual review of the generated texts. As a result, our evaluation relied solely on automated metrics and only a basic internal review by the authors, who lack medical expertise. This prevented the use of human-in-the-loop techniques such as reinforcement learning with human feedback, which could have iteratively improved the quality of the generated examples. The F1 scores well above 0.5 indicate that synthetic data remains somewhat distinguishable from real texts, suggesting that expert medical guidance could still meaningfully enhance generation realism.

6.4 Potential improvements

The prompt was the same for all thirteen LLMs and was primarily tested on `Llama-3-8B`. Hence, the performance might be biased towards the model. The method could be improved by tailoring the prompts to each model individually.

The evaluation of synthetic data sets could be further extended by checking for repeating examples in the synthetic data set or by checking how different the generated example is from the five provided examples. The evaluation could also be improved by checking for over-fitting to the original data set.

Furthermore, implementing adversarial fine-tuning approaches could improve the performance of our models and result in F1 scores closer to 0.5. This approach would involve training a classifier to detect synthetic examples and simultaneously improving the synthetic data generator to fool this detector by conducting error analysis of the classifier, leading to more realistic outputs.

7 Conclusion and future work

This paper presents a method for generating non-English synthetic medical data sets. To synthetically create data sets similar to the original, we carefully craft a prompt and perform pre-processing and post-processing of the data to increase performance and eliminate the effect of hallucinations.

Using a classifier and considering the inclusion of labels and generated text length, we conclude that `Llama-3.2-3B` is best for generating examples that most closely resemble the original data set. In the future, we plan to explore the underlying architectures of the models to understand their performance differences in multilingual contexts. This will allow us to refine our methods further and create more accurate data sets.

Furthermore, we intend to use the synthetic data set to train a named entity recognition (NER) system to recognize and extract medical labels from clinical history texts. To evaluate the effectiveness of this approach, we will compare the performance of NER models trained on synthetic data versus those trained on real data, using standard metrics such as precision, recall, and F1 score. This will allow us to assess how well the synthetic data preserves linguistic and semantic features necessary for downstream tasks. We also intend to create a more general pipeline enabling the code to generate synthetic medical data in various languages and formats.

Acknowledgement

This work was supported by the Slovenian Research Agency. Funded by the European Union. UK participants in Horizon Europe Project PREPARE are supported by UKRI grant number 10086219 (Trilateral Research). Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or European Health and Digital Executive Agency (HADEA) or UKRI. Neither the European Union nor the granting authority nor UKRI can be held responsible for them. Grant Agreement 101080288 PREPARE HORIZON-HLTH-2022-TOOL-12-01.

Appendix

A LLM Prompt

This section provides the prompt used in the study. The prompt oversaw many revisions and was tailored towards the `Llama-3.1-8B` model. Note that due to privacy concerns, the prompt shown here is changed such that the actual language used is replaced with the label `{target_language}`. We used 5 as our `{sample_size}` and a random label from our original data as `{random_label}`.

> You are a helpful AI assistant tasked with generating synthetic medical data based on provided template data.
>
> Your task is to generate a short medical history example (one example) in `{target_language}`, but in Latin script that includes the label "`{random_label}`". The provided text contains `{sample_size}` concatenated examples, separated by newlines. Your task is to create one example that is similar to the `{sample_size}` given examples. The generated example should be about `{random_int}` words long. Follow these specific

guidelines:

Generate one example only. DO NOT generate {sample_size} examples. The example should be similar to the {sample_size} given examples, but include the label "{random_label}". The following instruction is really important. Instruction: The text should not be more than {random_int} words long. The generated text should be really short. Ensure the label "{random_label}" is included exactly as shown, somewhere within the history. DO NOT CHANGE OR TRANSLATE THE label "{random_label}" in any way! The generated text MUST NOT exceed {random_int} words. Use commas and also rarely use // as separators. The text should be concise and formatted as a list, including diseases, medications, and relevant medical events, all on the same line. They have to be relevant, do not just generate random medical conditions. Use uppercase letters. The text should be in {target_language}, but written entirely in Latin script.

The goal is to create a realistic and concise medical history, including the label "{random_label}" somewhere in the text. Only output the generated text. DO NOT include any additional commentary, explanations, or formatting notes.

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Efficient and Secure Architecture for Mitigating DDoS Attacks in Software-Defined Vehicular Networks

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Keywords: ITS, SDN, SDVN, VANET, DDoS, IDS, snort, Mininet-Wifi, RYU controller

Received: December 27, 2024

Vehicular Ad Hoc Networks (VANETs) and Software-Defined Networking (SDN) have been combined to create SDN-enabled VANET architectures, which provide Intelligent Transportation Systems (ITS) with enhanced resource management, centralized control, and flexibility. However, the centralized control structure introduces new security challenges, notably Distributed Denial of Service (DDoS) attacks, which can significantly impact network stability and availability. In this study, we propose a DDoS detection framework for SDN-enabled VANETs, leveraging the Snort Intrusion Detection System (IDS) to effectively identify and mitigate DDoS threats. Our approach integrates Snort IDS into an SDN architecture based on the RYU controller, where Snort monitors network traffic for anomalies, and the SDN controller enforces dynamic mitigation strategies. The system is implemented using Mininet-WiFi, simulating a vehicular network environment with 10 vehicles nodes and a single RYU SDN controller. Performance evaluation under DDoS attack scenarios is conducted using the iPerf tool to measure key network metrics, including throughput, jitter, and packet loss rate. The results demonstrate that Snort IDS significantly improves network performance: jitter is reduced by up to 35%, packet loss rate decreases from over 40% to 15–25%, and throughput improves from 5–7 Mbps to a stable 10 Mbps. This study also explores the design and deployment of Snort within a Software-Defined Vehicular Network (SDVN) environment for effective DDoS detection and mitigation. By highlighting the importance of robust security mechanisms in SDN-enabled VANET architectures, this work contributes to the development of secure and reliable ITS infrastructures.

Povzetek: Članek predstavi varno SDVN arhitekturo z integracijo Snort IDS in RYU krmilnika za zaznavo DDoS napadov, kar izboljša prepustnost, zmanjša izgubo paketov in tresenje povezave.

1 Introduction

The rapid growth of Intelligent Transportation Systems (ITS) has sparked great interest in Vehicular Ad Hoc Networks (VANETs) as a vital technology for inter-vehicle communication and data exchange. VANETs, which are evolved from Mobile Ad Hoc Networks (MANETs), enable automobiles to act as mobile nodes, allowing for real-time information exchange that improves road safety, decreases traffic congestion, and improves the driving experience [1]. However, the dynamic and distributed nature of VANETs creates new issues for network management and security [2].

Software-Defined Networking (SDN) has emerged as a possible solution to some of the challenges associated with VANETs [3]. SDN offers centralized network management by divorcing the control plane from the data plane, as well as improving network flexibility and scalability. Integrating SDN with VANETs, resulting in an SDN-enabled VANET architecture, can improve traffic control, optimize resource allocation, and facilitate efficient routing. Despite these advantages, the centralized design of SDN creates weaknesses, most notably the possibility of Distributed Denial of Service (DDoS) attacks [4]. A DDoS attack on the SDN controller can jeopardize the overall stability and availability of the VANET network, posing a serious threat to ITS infrastructure [5].

To solve this issue, this paper presents a methodology for detecting DDoS attacks in SDN-enabled VANET infrastructures that employs the Snort Intrusion Detection System (IDS) [6]. Snort IDS is a powerful and popular program for monitoring network traffic and detecting potential security threats in real-time. Our approach uses Snort's capabilities to monitor network traffic patterns within the VANET, detecting odd behavior that could indicate a DDoS attack. The SDN controller enables rapid network response and coordination, allowing for timely threat mitigation [7].

In this paper, we present an in-depth analysis of DDoS attack detection in SDN-enabled VANETs, detailing the

integration of Snort IDS for enhanced network security. We conduct extensive simulations to evaluate the effectiveness of our proposed solution, demonstrating how Snort IDS can help maintain network stability and resilience against DDoS attacks. This research underscores the importance of robust security mechanisms in the future of ITS and contributes to the development of secure, efficient SDN-enabled VANET architectures. We measure throughput, jitter, and packet loss using widely accepted metrics before and after integrating Snort to assess its impact on network performance. Additionally, we explore the design and deployment of Snort within an SDVN environment to detect and mitigate DDoS attacks.

2 Background

In this section, we present the architecture of software-defined vehicular networks and their components, followed by a discussion of the security challenges associated with this architecture.

2.1 Software defined vehicular networks

Software Defined Vehicular Networks (SDVN) represent a transformative approach to managing and optimizing vehicular networks, which are essential components of modern ITS [8]. Traditional VANETs rely on decentralized architectures where each vehicle acts as a mobile node, communicating with other vehicles (V2V) or roadside infrastructure (V2I) [9]. While this decentralized structure allows for dynamic communication and data exchange on the move, it also presents challenges in terms of network management, scalability, and security [10]. This is where SDN comes into play, offering a centralized approach by separating the control plane from the data plane, thus allowing network intelligence and decision-making processes to be centralized in a single controller. In SDVN, the SDN controller can manage and coordinate vehicular network functions such as routing, traffic management, and security policies, making the network more flexible, adaptable, and easier to manage.

SDVN provides a centralized view of the entire vehicular network, allowing for real-time monitoring and control. This centralized control enables efficient traffic management, dynamic resource allocation, and optimized routing based on real-time conditions, which is particularly beneficial for densely populated urban areas prone to traffic congestion [11]. Moreover, SDVN architectures can enhance the deployment of safety-critical applications, such as collision avoidance systems, emergency vehicle prioritization, and efficient traffic light management, ultimately improving road safety and reducing response times during emergencies. SDN's programmability also allows for faster implementation of new applications and services tailored to the specific needs of VANETs without requiring changes to the underlying hardware infrastructure. As a result, SDVN can better support emerging applications in ITS, including autonomous driving, connected vehicles, and real-time traffic analytics [12].

However, while SDVN offers substantial benefits, it also introduces new challenges, particularly around security and resilience. The centralized SDN controller becomes a potential single point of failure and a prime target for cyber-attacks, such as DDoS attacks, which can disrupt the entire vehicular network [13]. To mitigate these risks, security mechanisms such as IDS, firewalls, and redundancy techniques need to be integrated into SDVN architectures. Additionally, the dynamic nature of vehicular networks where vehicles are constantly moving requires sophisticated and adaptive security and network management solutions that can handle rapid changes in network topology [14].

SDVN represent a promising evolution of vehicular networks, providing enhanced control, flexibility, and efficiency in network management. By enabling centralized control, SDVN facilitates efficient resource allocation and supports a wide range of ITS applications that improve road safety and traffic flow [15]. As the automotive industry moves toward more connected and autonomous vehicles, the importance of robust, scalable, and secure SDVN architectures will only continue to grow [16]. However, addressing the unique challenges of SDVN, particularly around security and scalability, will be critical to realizing the full potential of this innovative approach in the future of smart transportation [17]. Figure 1 shows the components of the SDVN architecture.

The SDN controller: is the central component of an SDN architecture, acting as the "brain" of the network. It enables centralized control and management of traffic, making decisions on data routing based on the network's needs. The controller communicates with network devices via protocols like OpenFlow, allowing dynamic and programmable network management. Examples of SDN controllers include RYU, OpenDaylight, and ONOS [18].

Northbound API: this interface connects the SDN controller to application-level services and allows it to translate high-level network policies into specific configurations for the underlying infrastructure. It plays a crucial role in enabling application developers to control and monitor network behavior without dealing with low-level network details.

Base Stations (BS): Positioned within the network infrastructure, base stations act as access points that connect vehicles and Road-Side Units (RSUs) to the SDN controller. These base stations ensure reliable communication between mobile nodes (vehicles) and the broader network, providing high-speed wireless links for data transmission.

OpenFlow RSUs: RSUs are fixed communication units deployed along roadsides or intersections. In this architecture, RSUs are OpenFlow-enabled, meaning they act as programmable switches that follow the instructions of the SDN controller. RSUs manage the interaction between vehicles and the network infrastructure, forwarding packets and optimizing data flow to ensure efficient communication [19].

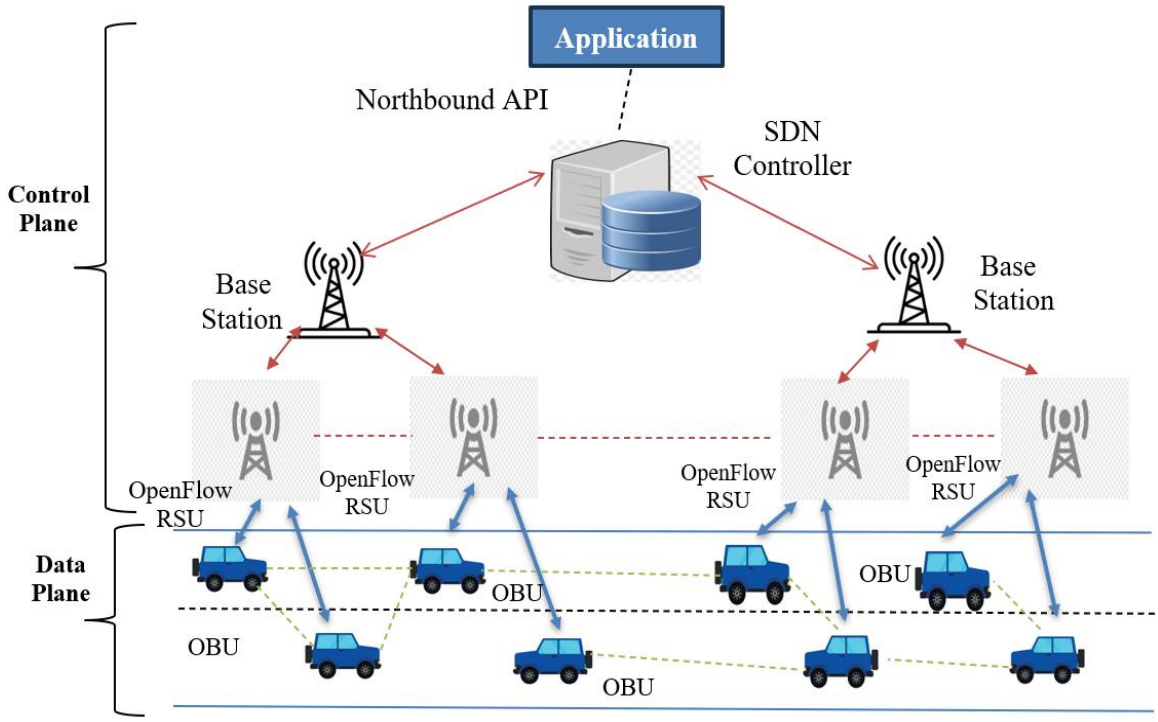


Figure 1: Software-defined vehicular network architecture

OBUs (On-Board Units): OBUs are installed in vehicles to enable wireless communication with RSUs and other vehicles. They support both Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication, allowing vehicles to share critical information such as safety alerts, traffic updates, and navigation data.

Application Layer: Located above the SDN controller, this layer hosts various network applications and services, such as traffic management systems, route optimization tools, and safety applications. These applications leverage the centralized control provided by SDN to analyze network data and optimize vehicular communication dynamically.

2.2 Network security in software defined vehicular networks

Network security in Software-Defined Vehicular Networks is crucial, as SDVNs introduce a new paradigm that enhances the flexibility and manageability of communications through centralized control. The integration of the SDN concept into vehicular networks enables dynamic and programmable network management, allowing for better traffic flow optimization and timely data distribution [20]. However, this shift towards a centralized control system introduces unique security challenges that require stringent measures to ensure safe operation. Cyber-attacks, such as DDoS attacks, can exploit the SDN controller's centralized nature, potentially disrupting communications critical to vehicle safety and traffic management. Moreover, due to the mobility and highly dynamic nature of vehicular networks, ensuring real-time, secure communication between vehicles and infrastructure becomes complex, necessitating robust intrusion detection systems and intelligent threat mitigation strategies. Intrusion detection systems like Snort can play a significant role in identifying and countering threats by analyzing traffic patterns and detecting anomalies [21].

The controller's centralized structure in SDVNs makes it both a key component and a potential single point of failure, subject to different cyberattacks such as DDoS attacks, spoofing, and malware injection. The dynamic and highly mobile nature of vehicular networks complicates security even more, as vehicles join and depart the network on a regular basis, opening up new attack routes [22]. Furthermore, the sharing of sensitive data, such as location information and driving behavior, emphasizes the importance of secure communication protocols and encryption technologies for protecting user privacy [23].

2.3 Related work

Table 1 presents a comparative analysis of recent works on DDoS detection frameworks in SDN based VANETs, highlighting the detection methods, tools used, platforms, and evaluation metrics. This comparison underscores the novelty and practical effectiveness of our approach in addressing real-time SDVN security challenges through measurable network performance indicators.

Table 1: Comparative analysis of existing works on SDN based VANETs security

Study	Detection Method	IDS Tool	Platform	Metrics Employed
Türkoğlu et al. [24]	ML (KNN, SVM, DT) + MRMR + Bayesian Optimization	Custom ML pipeline	SUMO + Mininet-WiFi + POX + sFlow + InfluxDB (SD-VANET)	Accuracy (99.35%), Sensitivity, Specificity, F1-score
Elubeyd & Yiltas-Kaplan [25]	Hybrid DL (1D-CNN + GRU + DNN)	Custom DL model	RYU + Mininet + OVS (Colab), CICDDoS2019 & synthetic data	Accuracy (99.88%), Precision, Recall, F1-score, ROC-AUC
Setitra & Fan [26]	Optimized TabNet + Adam + GSCV	Opt-TabNet	Mininet + RYU with SDN-DDoS & InSDN datasets	Accuracy (99.42%), Precision, Recall, F1-score
Ma et al. [27]	RF with Heterogeneous Integrated Feature Selection + Edge/Distributed Computing	EDRFS (edge-deployed RF model)	CIC-DDoS2019 on SDN with distributed controller simulation	Accuracy (99.99%), Precision, Recall, F1-score, Prediction time (0.4s)

Compared to existing studies that primarily rely on machine learning or deep learning techniques for DDoS detection in SDN environments, the proposed approach distinguishes itself by integrating a signature-based Snort IDS with a RYU SDN controller for real-time anomaly detection and mitigation. While previous works focus on achieving high detection accuracy using offline datasets like CICDDoS2019 or NSL-KDD, they often lack real-world deployment and runtime traffic evaluation. In contrast, this study implements a practical, real-time defense system within a simulated vehicular network using Mininet-WiFi, where performance under DDoS attacks is assessed using network-level metrics such as throughput, jitter, and packet loss. This combination of signature-based detection, SDN programmability, and real-world traffic analysis offers a more deployable and responsive solution, especially suited for dynamic and latency-sensitive environments like vehicular networks.

3 Proposed scheme

This article focuses on cyber-attacks, with a special emphasis on the impact of DDoS assaults on SDVNs [28]. These attacks are primarily intended to impair network performance, cause disruptions, and undermine the centralized management and control of network resources. This is accomplished by dividing the network's design into two planes: control and data [29]. SDVNs provide benefits like as flexibility and scalability, but they also pose new security concerns. DDoS assaults are particularly significant risks to SDVNs, as a massive flood of malicious traffic can disable network resources and disrupt vital services. DDoS assaults have serious consequences for SDVN networks, resulting in performance deterioration, network unavailability, and significant financial ramifications.

In the fight against network threats, IDS serve as critical defenses. Snort, a renowned open-source IDS, exemplifies this approach to network security. It monitors network traffic by combining packet sniffing with signature-based detection to identify potential threats and intrusions [30]. Acting as an IDS, Snort continuously inspects traffic and compares it against predefined rules and signatures. These rules define behavioral patterns associated with known attacks or malicious activities. When a match is found, Snort generates alerts or logs detailed information, providing a comprehensive report on the suspected intrusion. Through deep packet inspection of network protocols and payloads, Snort effectively detects various types of attacks. These capabilities collectively fortify SDVN against threats targeting switches, controllers, and communication links

This section further explores the design and deployment of Snort within an SDVN environment to detect and mitigate DDoS attacks

3.1 System modeling

Snort was selected as the IDS for this study due to its lightweight architecture, open-source availability, and proven effectiveness in detecting a wide range of DDoS attack signatures [31]. Its design aligns well with the computational constraints typical of vehicular nodes and edge environments in SDVNs. Compared to alternatives such as Suricata, which offers multi-threaded packet processing for high-throughput applications, and Zeek, which provides deep contextual and behavioral traffic analysis, Snort offers simpler configuration and lower resource overhead. These features make it a practical choice for latency-sensitive environments where computational efficiency and ease of integration are critical. Additionally, Snort benefits from an active community, a rich rule set, and smooth interoperability with SDN architectures through log parsing and alert generation.

In our deployment, Snort was configured to detect common and disruptive DDoS attack types in vehicular

networks, specifically UDP and TCP floods, chosen for their prevalence and impact on bandwidth and latency in mobile scenarios. Upon detection, Snort generates alerts that the Ryu SDN controller interprets to modify flow rules. A priority-based flow table distinguishes confirmed threats, suspicious activity, and normal traffic: high-priority rules immediately block or reroute malicious flows, medium-priority rules flag questionable behavior for monitoring, and low-priority rules manage standard forwarding. This approach enables real-time mitigation without disrupting legitimate communication, with rule timeouts preventing table overflow.

Although Suricata's multi-threading and Zeek's behavioral analysis offer potential advantages in throughput and detection of unknown attacks, they often demand more resources and complex configuration. Integrating Snort with the SDN controller and prioritizing efficient flow rule management presents a practical and effective security solution for SDVNs, balancing reliability and latency requirements in performance-critical ITS environments [32].

The suggested system contains a DDoS attack detection and mitigation method by incorporating an IDS into the SDN architecture, which is intended for usage in both home and business networking settings [33]. The system functions on a feedback loop that includes three major architectural components: the network, the IDS, and the controller [34]. The network depicts all data flow and the point at which a DDoS attack could be initiated. The IDS detects DDoS attacks by analyzing all network traffic. When the IDS identifies an ongoing DDoS attack, it alerts the controller. Once the IDS alerts, the controller sends new flow rules to network devices along the data channel to restore normal network functioning as soon as possible (Figure 2).

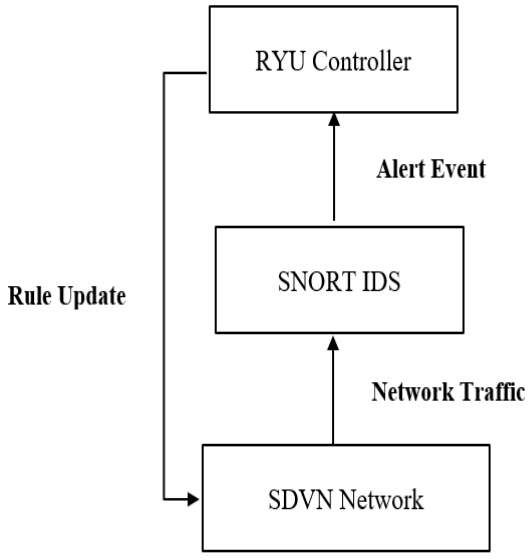


Figure 2: System architecture design

3.2 System deployment

The system comprises three important phases: detection, communication, and mitigation. The detection phase focuses on the system's ability to detect DDoS attacks. The communication phase happens when the IDS notifies the controller of the observed DDoS attack. The mitigation phase occurs when the controller applies specific flow rules to the local switch, preventing harmful traffic. These flow rules are stored permanently in the switch.

Figure 3 illustrates the conceptual model and workflow of the proposed system, which integrates an SDN controller with an Intrusion Detection System (IDS) to form an SDN-Based IDS Monitor for detecting and mitigating DDoS attacks. When a new packet enters the system, it is classified as part of a flow. The OpenFlow switch first checks its flow table for a matching rule. If a rule exists, the packet is forwarded to its destination. If no rule is found, the switch queries the SDN controller for further instructions. Simultaneously, the packet is analyzed by the IDS, such as Snort, which classifies flows as "good" or "malicious" based on predefined rules. If the IDS identifies a packet as part of an attack, it alerts the SDN controller, which responds by installing a blocking flow rule in the switch to discard packets from the malicious flow. For legitimate packets, the SDN controller configures the switch with appropriate forwarding rules, ensuring they reach their destination. This coordinated approach enables real-time detection and mitigation of malicious traffic while maintaining efficient and secure network operations

This diagram in figure 4 presents the series of events in an SDN-based automotive network that processes ICMP Echo Requests while incorporating Snort IDS and the RYU controller. The car sends an ICMP Echo Request, which is routed through the switch and NAT before reaching the server. In addition, a copy of the request is transmitted to Snort IDS for examination. If the IDS detects any malicious activity, it alerts the RYU controller, urging it to create a flow rule to prevent malicious traffic. The server validates the valid ICMP request and sends an ICMP Echo Reply back to the vehicle via the network channel, ensuring secure and efficient communication.

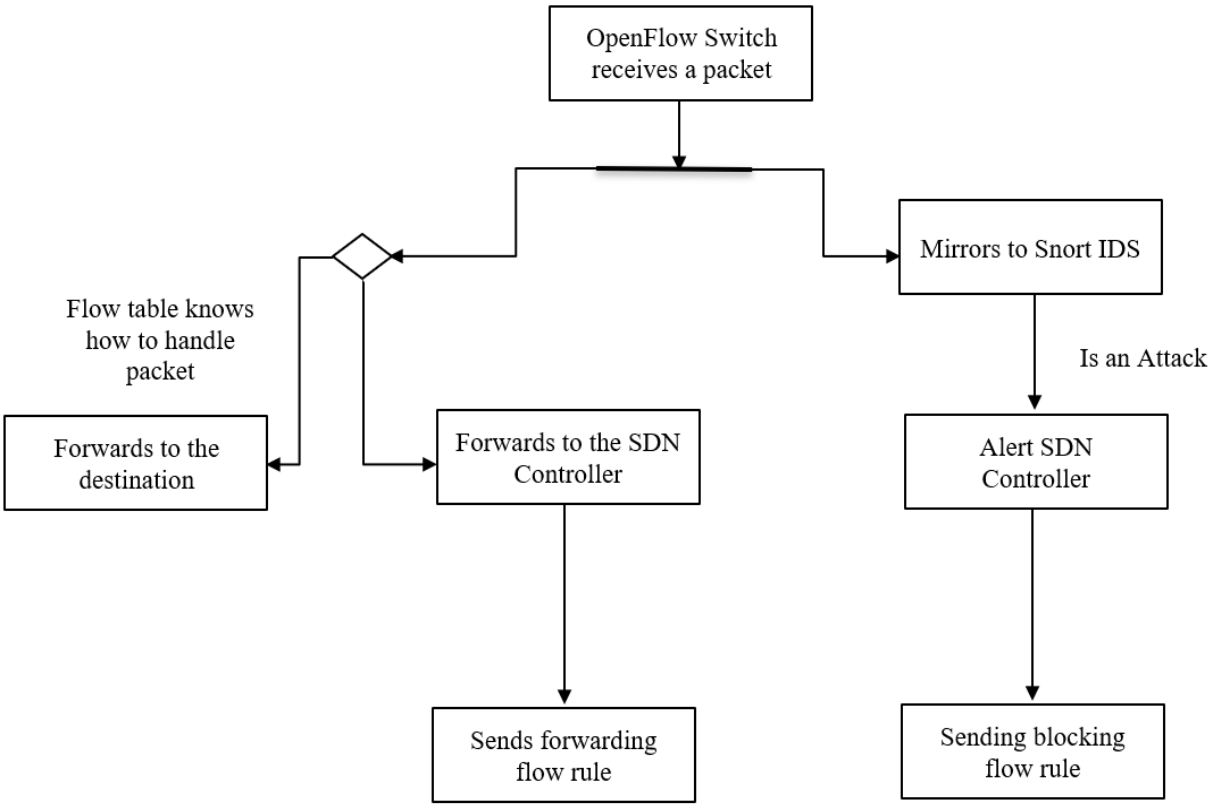


Figure 3: System workflow

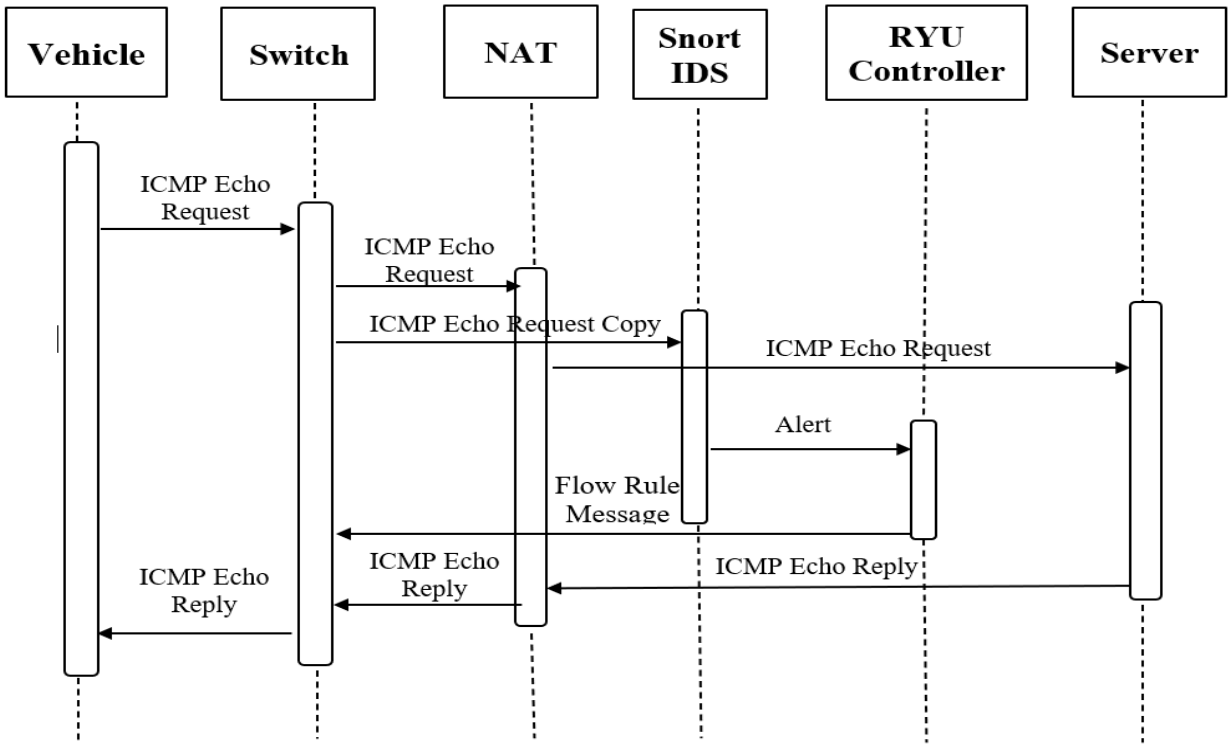


Figure 4: System message sequence diagram

4 Results and discussion

In this simulation, we carry out a DDoS attack on an SDVN network and include the Snort intrusion detection system. We then collect data before to and following the implementation of the Snort IDS.

4.1 Experiment configuration

Our experimental system was installed on a server running Ubuntu 20.04, with an Intel(R) Core (TM) i7-1165G7 CPU @ 2.80 GHz and 16 GB RAM.We used Mininet-WiFi [35] with the RYU controller to simulate a vehicular network consisting of 10 nodes representing vehicles [36]. The RYU controller and switches communicated using the OpenFlow protocol (version 1.3) [37]. We employed hping3 to simulate various DDoS attack types, including TCP flood and UDP flood attacks. This setup allowed us to rigorously evaluate the robustness of our DDoS detection framework by assessing Snort IDS's detection and mitigation capabilities under diverse threat scenarios. Additionally, iPerf was used to evaluate throughput, jitter, and packet loss, providing reliable performance metrics for analysis [38].

To create our SDN-based IDS, we merged the capabilities of an SDN controller and an IDS. The SDN controller in our configuration is based on RYU, an open-source Python framework. Within this controller, we created a Python method called process_snort_alert to handle IDS alerts. When an alert is identified as a "RYU block," the function sends a flow rule to the switch to prevent malicious traffic; otherwise, it ignores the traffic. For the IDS, we employed Snort, a widely used tool for detecting attacks through predefined rule signatures. We customized Snort by modifying the snort.conf file and adding specific DDoS detection rules in the ddos_detection.rules file. These rules were designed to address the DDoS attack scenarios tested in our setup, demonstrating the flexibility of our solution to handle different types of DDoS cyber-attacks.

4.2 Performance evaluation

The analysis highlights the impact of integrating Snort IDS on jitter behavior in an SDVN network. Without Snort IDS, jitter increases sharply and fluctuates widely, indicating network instability and inconsistent packet delivery, which can degrade the quality of service, particularly under attack conditions such as DDoS. In contrast, with Snort IDS, jitter remains stable and significantly reduced, demonstrating improved network performance through reduced delay variability and consistent packet delivery.

This is further illustrated in the figure 5, which compares jitter over a time period. The jitter without Snort IDS reflects network instability, while the jitter with Snort IDS highlights a more stable and resilient network. The integration of Snort IDS effectively mitigates the impact of attacks by detecting anomalies and applying countermeasures, enhancing the stability and reliability of SDVN environments.

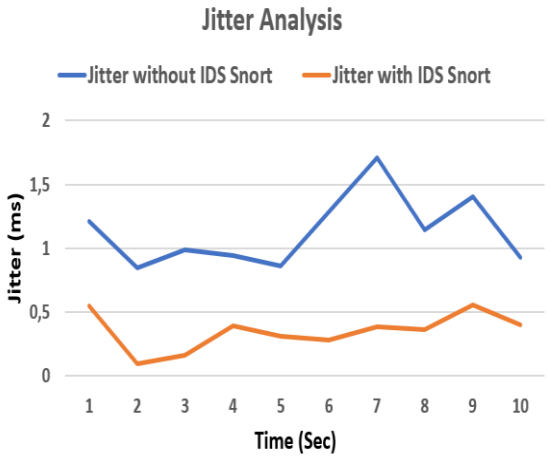


Figure 5: Comparison of Jitter in SDVN scenarios: with and without IDS Snort integration

Figure 6 show the impact of Snort IDS on the Packet Loss Rate (PLR) in the network. Without Snort IDS, the PLR is significantly higher, often exceeding 40%, indicating the adverse effects of undetected DDoS attacks, including resource overload and severe performance degradation. In contrast, with Snort IDS, the PLR is significantly reduced, typically ranging from 15% to 25%. These results highlight Snort's effectiveness in detecting and mitigating DDoS attacks by efficiently managing network traffic, thereby reducing packet loss and improving network reliability and performance.

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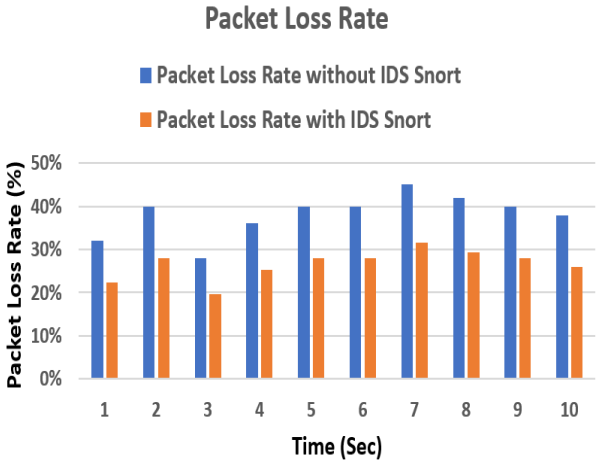


Figure 6: Comparison of Packet loss rate in SDVN scenarios: with and without IDS Snort integration

Figure 7 presents the impact of Snort IDS on network throughput. Without Snort IDS, the throughput remains low, fluctuating between approximately 5 Mbps and 7 Mbps, reflecting the effects of a DDoS attack that disrupts data transmission and overloads the network. In contrast, with Snort IDS, the throughput is consistently higher and stable, reaching nearly 10 Mbps. These results

demonstrate that integrating Snort IDS enhances network performance by effectively filtering malicious traffic, reducing congestion, and ensuring resource availability for legitimate users. This leads to a more reliable and high-performing network.

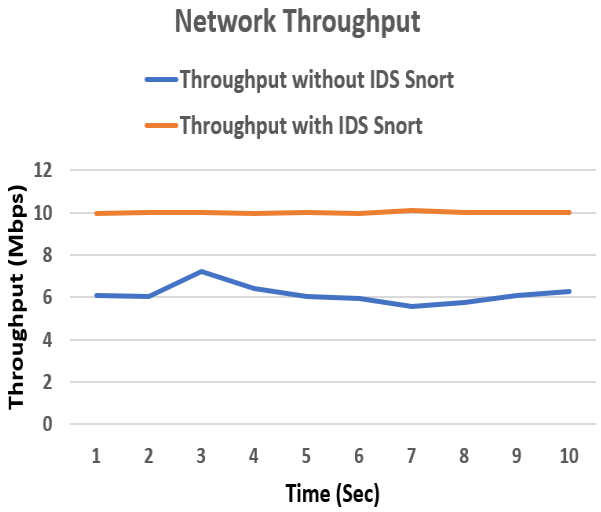


Figure 7: Comparison of throughput in SDVN scenarios: with and without IDS Snort integration

The assessment of network performance shows how implementing the Snort IDS has major advantages. Snort IDS continuously increases network efficiency and dependability across three important metrics: jitter, throughput, and packet loss rate. Throughput is increased, guaranteeing faster and more reliable data transmission rates; jitter is reduced, offering smoother performance for latency-sensitive applications; and packet loss is decreased, improving data delivery. These findings demonstrate that Snort IDS is a useful tool for performance optimization in real-time and high-demand network contexts since it not only improves security by thwarting possible threats but also raises network quality generally.

4.3 Discussion

The experimental results demonstrate the effectiveness of integrating Snort IDS in enhancing the stability and performance of SDVNs under DDoS attack scenarios. The inclusion of Snort leads to measurable improvements in key network metrics, including reduced jitter, decreased packet loss, and increased throughput. These outcomes validate Snort's role in real-time traffic monitoring and anomaly detection, contributing to improved network resilience in dynamic vehicular environments.

While these improvements—such as jitter reduction by up to 35%, packet loss rate reduction to 15–25%, and throughput stabilization around 10 Mbps—are significant, it is important to contextualize them within the demands of real-world ITS. Although reducing packet loss from over 40% to as low as 15% represents a substantial enhancement, a 25% loss rate remains relatively high for safety-critical applications. In scenarios like collision avoidance or emergency coordination, even minor packet loss or jitter can compromise communication reliability and jeopardize safety. Therefore, while Snort enhances baseline network stability, additional mechanisms—such as traffic prioritization, redundant paths, or edge-assisted processing—may be needed to meet the strict real-time requirements of modern ITS environments.

While Snort performs reliably in this context, its signature-based detection approach limits its ability to identify novel or zero-day attacks. By contrast, IDS solutions such as Suricata offer multi-threaded packet processing and higher throughput capabilities, while Zeek provides deeper contextual and behavioral traffic analysis. However, these alternatives often require more computational resources and involve more complex configurations. For lightweight and latency-sensitive environments like VANETs, Snort represents a practical trade-off between detection capability and system simplicity.

Nonetheless, Snort introduces computational overhead due to deep packet inspection and rule-based evaluation. Although resource limitations were not a bottleneck in the current simulation, real-world deployments—particularly in high-density or resource-constrained settings—may face scalability challenges. Addressing these issues may require lightweight or distributed IDS implementations, potentially integrated with fog or edge computing architectures to ensure sustained performance under load.

Another key consideration is that Snort's detection effectiveness strongly depends on the quality and relevance of its rule sets. A high false positive rate can result in unnecessary traffic blocking or mitigation actions, thereby reducing overall network efficiency. To mitigate this, effective rule tuning is essential. Future enhancements could involve automated rule optimization or the incorporation of machine learning-based anomaly detection to improve adaptability and responsiveness in dynamic vehicular scenarios. In summary, while Snort proves to be a viable and efficient solution for SDVN security enhancement, future research should focus on hybrid IDS frameworks and resource-aware deployment strategies to overcome scalability and detection limitations in real-world VANET implementations.

5 Conclusion

This study examined the detection and mitigation of DDoS attacks in SDVN networks using Snort IDS. By simulating a DDoS attack and analyzing network performance—jitter, packet loss, and throughput—before and after integrating Snort IDS, we observed significant improvements in network stability. The integration of Snort IDS resulted in reduced jitter, lower packet loss, and more consistent throughput, demonstrating its effectiveness in enhancing the resilience of SDVN networks against DDoS attacks. The IDS quickly detects and mitigates attacks, ensuring reliable communication and improved service quality. Additionally, the implementation of Snort IDS in an SDN-based VANET showed significant benefits in network performance, such

as reduced packet loss, increased throughput, and minimized jitter. These improvements are vital for the latency-sensitive nature of VANETs, where reliable communication is crucial for road safety and intelligent transportation applications. The use of SDN further enhances traffic management and centralized control, complementing the effectiveness of Snort IDS. This study emphasizes the combined benefit of SDN and IDS technologies in improving both security and performance in next-generation vehicular networks.

Future work will focus on enhancing the scalability, resilience, and intelligence of the proposed framework to support real-world deployment in large-scale VANETs. Although our experiments were conducted in a simulated environment, the modular design of SDN and Snort IDS enables distributed deployment across roadside infrastructure and vehicular edge nodes. To improve fault tolerance and reduce control latency, we plan to integrate a multi-controller SDN architecture, ensuring load balancing and redundancy across dynamic network regions. Precise benchmarking of alert-to-response latency using tools like tcpdump and controller logs will also be conducted to evaluate real-time mitigation capabilities. Additionally, we aim to incorporate entropy-based metrics for lightweight, dynamic anomaly detection and explore hybrid detection approaches that combine statistical analysis with machine learning models, such as Random Forest or SVM, to improve detection accuracy and adaptability. Context-aware detection and behavioral profiling of vehicles will further enhance the system's ability to distinguish between benign and malicious traffic in real-time ITS scenarios.

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Hierarchical Feature Fusion With Inception V3 for Multiclass Plant Disease Classification

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Keywords: plant disease detection, deep learning in agriculture, hierarchical feature fusion, convolutional neural networks, multi-class classification, inception v3, swish activation function, global average pooling

Received: February 5, 2025

Artificial Intelligence (AI) and Deep Learning (DL) are revolutionizing plant disease detection, which is crucial for mitigating crop loss, improving food security, and enhancing yield. Traditional manual methods, such as field visits for disease diagnosis, are labor-intensive, time-consuming, and costly, highlighting the demand for automated, real-time applications. However, plant disease classification faces challenges such as class variations, cluttered backgrounds, lesion scale variations, and the need for robust models. Several Convolutional Neural Network (CNN)-based frameworks have been proposed to tackle these challenges, but they often suffer from limitations such as fixed-size kernels and inefficient feature utilization across deeper layers. These limitations lead to feature loss during the initial stages of feature extraction, reducing the model's overall effectiveness in multi-class plant disease classification. To address these issues, we introduce HFFIncep-Net, a novel Deep Learning framework that fuses hierarchical features with the power of the Inception V3 architecture. The Hierarchical Feature Fusion (HFF) stem extracts multiscale features, which are fused at multiple levels within the network. This enhances feature representation and mitigates information loss in the initial layers. Incorporating two Inception V3 blocks, the model captures a diverse set of features at different scales, further improving classification performance. Additionally, the inclusion of a Global Average Pooling (GAP) layer reduces computational complexity while maintaining high accuracy. To enhance training stability and performance, we employ the Swish activation function, which facilitates smoother gradient propagation during backpropagation. When evaluated on the PlantVillage and Cassava Leaf Disease (CLD) datasets, HFFIncep-Net achieves 94.61% precision, 94.31% recall, 94.31% F1 score, and 97.80% accuracy, outperforming existing CNN-based methods. These results demonstrate that HFFIncep-Net is an effective solution for early-stage, multi-class plant disease classification, with significant potential for practical deployment in agricultural applications.

Povzetek: Članek predstavi model HFFIncep-Net, ki z večnivojsko fuzijo značilk in izboljšano arhitekturo Inception V3 natančno klasificira več vrst bolezni rastlin kljub vizualnim in merskim variacijam.

1 Introduction

Agriculture serves as the foundation of the food distribution network[1], and the financial systems of many developing nations rely heavily on it [2]. The prevalence of plant diseases significantly impacts crop health and diminishes yields, leading to substantial losses [3]. Such yield reductions can have a ripple effect on the food supply network and the nation's economy. Plant diseases are typically caused by various agents, including viruses, bacteria, parasites, fungi, or environmental factors. Many cultivators may be unaware of certain types of plant diseases[4]. Recognizing plant diseases in their early stages is crucial for controlling outbreaks and preventing extensive damage to crops [5]. To effectively handle these disease occurrences, regular discussions with specialists are crucial. Nevertheless, regular visual evaluations by specialists in isolated regions of developing countries tend to be costly, less accurate, and time-consuming. Therefore, automatically identifying crop disease symptoms present a valuable, quick, and cost-effective solution [6].

Typically, the symptoms of crop diseases manifest on the leaves, creating digital representations of leaves makes them ideal contenders for identifying plant diseases. In recent years, various intelligent systems have been developed for crop disease diagnosis, which can be categorized into two main types: (i) Traditional computer vision-based detection [6] and (ii) Deep learning-based detection [7]. Standard systems depend on feature extraction and classification approaches. Over the past few decades, numerous feature extraction methodologies, such as Local Binary Patterns (LBP) [8], Scale-Invariant Feature Transform (SIFT) [9], Speeded Up Robust Features (SURF) [10] [11], Histogram of Oriented Gradients (HOG) [12], and Gabor Transform (GT) [13],

have been employed. At the same time, machine learning classifiers, including Support Vector Machine (SVM) [11], Naive Bayes (NB) [14], Random Forest (RF) [14], and Fisher Linear Discriminant (FLD) [15], have been utilized for classifying plant diseases. The precision of traditional diagnostic systems is significantly dependent on the manually crafted feature extraction techniques and classification algorithms employed. Importantly, choosing optimal and resilient handcrafted features for disease identification is especially difficult as each feature comes with its own shortcomings, such as region of interest, scale variation, illumination variation, inter and intra class variation, and dead neurons.

Lately, with the emergence of domain-specific architectures[16] such as GPUs, TPUs, and similar technologies, Deep Learning (DL)-based classifiers, specifically CNNs, have gained significant popularity. A variety of CNN-based models, such as PDD-Net, VGG-16, AlexNet, Inception V3, and ResNet-50 are adept at automatically extracting and learning the best low-level features for classification tasks [17]. These CNN architectures have demonstrated strong efficiency in image classification tasks. However, despite their effectiveness, real-time plant disease categorization faces several obstacles, including early-stage diagnosis, variations in disease classes, limited sample sizes in benchmark datasets, and class imbalance issues[18].

To overcome these issues, this study introduces a blended CNN architecture that leverages recent advancements in the field. The proposed model includes three pooling blocks to boost the retrieval of both local and global multiscale features, enhancing accuracy in identifying small-scale lesions. Furthermore, a dense connection block is associated to promote the flow of information across network layers, thereby enhancing multilevel feature extraction. To reduce model complexity, a GAP layer replaces fully connected layers. The Swish activation function is applied to address potential issues such as gradient vanishing, often linked with traditional activation functions during backpropagation. Swish enhances convergence during training, leading to better performance. HFFIncep-Net is evaluated using the publicly available PlantVillage dataset containing five different plants and nineteen disease classes and CLD dataset containing 5 classes of Cassava leaves demonstrating significant enhancements in classification accuracy when contrasted with the state-of-the-art CNN-based architecture. This study highlights the following significant advances targeted at solving the inadequacies of current computer vision systems for plant disease detection:

- The HFFIncep-Net CNN-based framework employs bicubic interpolation to handle constrained data, reduce information loss, and enhance training efficiency.
- The architecture includes multilevel and multiscale features, a reliable Swish activation function, and GAP layer to improve overall performance and mitigate errors such as overfitting and gradient vanishing.
- HFFIncep-Net outperforms baseline models such as PDD-Net, DenseNet-201, ResNet-50, AlexNet, MobileNet, and Inception V3 as evidenced by assessment criteria such as accuracy, precision, recall, and F1-score.

This work makes an important contribution to the development of a strong and effective Plant Disease Diagnosis system that effectively detects plant disease and manages variations in disease classifications. The paper is structured as follows: Section 2 provides a literature review on the current state-of-the-art frameworks for plant disease diagnosis. Section 3 describes the materials and techniques utilized in the study, including an in-depth discussion of the proposed HFFIncep-Net architecture. Section 4 explains a full review of the experiments and results. Section 5 summarizes the basic conclusions of the article and suggests possibilities.

2 Literature review and analysis

Over the last decade, several CNN-based frameworks for plant disease detection have been proposed. Alghamdi et al. [19] utilized VGG16 as the baseline architecture and proposed PDD-Net, which integrates multilevel and multiscale CNN features within the VGG16 model. Their approach introduced dense connection blocks to extract multilevel features and a spatial pyramid block to capture multiscale features. These modifications demonstrated that multilevel features are essential for addressing class variations, while multiscale features effectively handle Region of Interest (RoI) scale variations. To further enhance performance, PDD-Net employed the flattened Threshold Swish (fTS) activation function to mitigate gradient vanishing and dead neuron issues. Additionally, the final layer of PDD-Net replaced the fully connected layer with a GAP layer, which reduced the overall number of parameters and minimized overfitting. Although the proposed framework achieved robust results on the PlantVillage and CASSAVA benchmark datasets, PDD-Net utilized the simple feed-forward stem of VGG16, which led to information loss in the deeper layers of the network [20].

Keceli et al. [21] focused on the development of automated methods to enhance the recognition of plant species and the detection of plant diseases. A novel approach is presented that utilizes a multi-input, multi-output CNN integrating raw image data with pre-trained features derived from the AlexNet model. The proposed architecture incorporates convolutional, pooling, and fully connected layers to support accurate classification. The study employed the ReLU (Rectified Linear Unit) activation function within the convolutional layers, though this approach can lead to issues such as gradient vanishing, while classification tasks are handled by fully connected layers culminating in a SoftMax layer. The model employs a categorical cross-entropy loss function to address both species classification and disease detection tasks,

combining the two loss values through a weighted approach to optimize learning. Two datasets were utilized for validation: the PlantVillage dataset, and the FISB dataset, which contains real-world agricultural images. By using AlexNet as a feature extractor, the model benefits from reduced computational complexity and shorter training times due to its relatively low parameter count. The findings demonstrate the model's effectiveness, achieving high accuracy rates: 98% for plant type and health status classification, and 89% for disease classification on the PlantVillage dataset. Similarly, on the FISB dataset, the model achieved 97% accuracy for plant type classification and 94% for disease detection. This study emphasizes the advantages of employing a multi-task learning approach, outperforming single-task frameworks in various metrics such as accuracy, precision, recall, and F1 score.

Chen et al. [22] introduced MS-DNet, a novel lightweight neural network designed for crop disease recognition. Building upon DenseNet, MS-DNet incorporates in depth wise separable convolutions (DSC) and Squeeze-and-Excitation (SE) blocks to enhance feature extraction while reducing model complexity. Preprocessing steps involved converting images to RGB color space, resizing them to 224×224 pixels, and augmenting the dataset using traditional methods (rotation, flipping) and generative adversarial network-based augmentation. The network employed ReLU activation functions in dense blocks and a SoftMax classifier for multi-class classification, utilizing a modified Focal Loss function to handle class imbalance.

Sutaji & Yıldız. [23] proposed LEMOXINET, an ensemble model combining MobileNetV2 and Xception architectures to enhance plant disease detection performance. By concatenating features extracted from both networks, the model aimed to improve accuracy while maintaining computational efficiency. Preprocessing included resizing images to 224×224 for MobileNetV2 and 299×299 for Xception, normalizing pixel intensity values, and augmenting training data with various transformations to simulate different image conditions. The model utilized ReLU activation functions in initial layers and SoftMax in the final classification layer. The model was evaluated on datasets such as iBean, citrus, rice, and Turk-Plants.

Sanida et al. [24] proposed an architecture to improve tomato disease identification by employing a two-stage transfer learning approach to reduce training time and enhance accuracy. Their model integrated the first ten layers of VGG16 with two inception blocks, resulting in a significantly smaller network than the standard VGG16. Images from the PlantVillage dataset were resized to 224×224 pixels and split into training, validation, and testing sets (70%, 20%, and 10% respectively). An enhanced categorical cross-entropy loss function addressed class imbalance during training.

Paul et al. [25] presented a lightweight custom CNN and leveraged transfer learning models VGG-16 and VGG-19 to classify tomato leaf diseases across 11 classes. Preprocessing involved converting images to JPEG format and resizing them to 224×224 pixels. The custom CNN used the SoftMax activation function in the final layer and employed categorical cross-entropy as the loss function.

Zhou et al. [26] presented a restructured residual dense network (RRDN) to improve tomato leaf disease identification. By integrating the strengths of deep residual and dense networks, RRDN reduced training parameters and enhanced the flow of information and gradients. Preprocessing involved resizing images to 196×196 pixels and normalizing pixel values. The network utilized a 3-layer Residual Dense Block (RDB) with ReLU activation after each convolution and Leaky ReLU post-normalization to mitigate the dead neuron phenomenon. A cross-entropy loss function was employed alongside a SoftMax activation in the output layer for multi-class classification. Evaluated on the AI CHALLENGER dataset containing 13,185 images across 9 classes, RRDN achieved 95% accuracy on both validation and test sets, demonstrating its efficacy in disease identification.

Paymode & Malode. [27] focused on detecting and classifying diseases in crops, particularly tomatoes and grapes, using a Convolutional Neural Network (CNN) based on the VGG16 architecture. Image preprocessing included filtering, grayscale transformation, sharpening, and scaling. Data augmentation techniques such as rotation, translation, and random transformations were applied to enhance the dataset's diversity. The model employed ReLU activation functions and a SoftMax activation in the final layer for classification. Utilizing the PlantVillage dataset, which comprises 54,303 high-quality images across 38 crop classes, the proposed CNN achieved remarkable accuracies of 98.40% for grapes and 95.71% for tomatoes.

Pan et al. [28] introduced TFANet, a two-stage feature aggregation network designed for multi-category soybean leaf disease identification. The model aimed to capture intricate features by aggregating information at different stages. Preprocessing steps involved resizing images to 224×224 pixels and applying extensive image augmentation techniques, including rotation, flipping, color dithering, brightness enhancement, Gaussian noise addition, and adaptive histogram equalization. The model utilized the Sigmoid activation function and employed cross-entropy as the loss function for training. Evaluated on the Auburn Soybean Disease Image Database (ASDID) containing 9,648 images, TFANet demonstrated high efficacy with an accuracy of 98.18%, precision of 98.21%, recall of 98.60%, and an F1-score of 98.39%.

Zhang et al. [29] proposed SDINet, a Siamese Dilated Inception Network tailored for apple leaf disease detection using minimal training samples. The model leverages dilated convolutions within Inception modules to capture multiscale features. Extensive data augmentation was performed, generating 10 augmented images per original through cropping, rotation, rescaling, flipping, brightness adjustment, contrast changes, noise addition, saturation, light enhancement, and random erasing. Images were resized to 256×256 pixels. ReLU activation functions were applied after each convolutional layer and dilated Inception module to enhance nonlinearity. Evaluated on the AppleDisease5 dataset comprising 2,000 images

across five disease classes, SDINet achieved an accuracy of 94.11%, precision of 93.58%, recall of 92.80%, and an F1-score of 93.19%. The model contains fewer than 10 million parameters, significantly less than traditional models like AlexNet.

Dai et al. [30] proposed the DFN-PSAN model, a multi-level deep information feature fusion extraction network designed for plant disease detection in natural field environments. The model integrates a position-sensitive attention mechanism (PSA) to enhance feature representation while reducing parameters by 26% compared to optimal attention mechanisms. Preprocessing steps included converting images to RGB format, resizing to 256×256 pixels, and applying Gaussian filtering and non-local means noise reduction. Weather data augmentation simulated various environmental conditions such as fog, illumination changes, and raindrops to improve robustness. The network utilized ReLU activation in convolutional layers and Sigmoid in attention layers, with a SoftMax classifier at the output. Using cross-entropy loss with label smoothing, the model was trained on datasets like Katra-Twelve, BARI-Sunflower, and FGVC8. DFN-PSAN achieved accuracy of 98.37%, 94.23%, and 93.24% on these datasets respectively, with overall performance exceeding 95.27%.

In another research Dai et al. [31] presented PPLC-Net, a neural network-based model for plant disease detection enhanced by Weather-based data augmentation and a multi-level attention mechanism. The model incorporates dilated convolutions and GAP layers to improve feature extraction. Images were cropped to 256×256 pixels with adaptive scaling. Cross-entropy loss function was employed during training. Evaluated on a dataset of 4,503 images covering 22 leaf classes from 12 plant types, PPLC-Net achieved an impressive accuracy of 99.702%, precision of 98.545%, recall of 98.340%, and an F1-score of 98.442%. With 15.486 million parameters, the model balances complexity and performance in plant disease classification.

Thakur et al. [32] presented VGG-ICNN, a lightweight Convolutional Neural Network designed for crop disease identification using plant leaf images. The model combines the initial four convolutional layers of a pre-trained VGG16 with three blocks of GoogleNet Inception v7, resulting in approximately 6 million parameters significantly fewer than many high-performing models. Preprocessing involved resizing images to 224×224 pixels and normalizing pixel values. The dataset was split into training, validation, and test sets. ReLU activation functions were applied within the Inception blocks, and a SoftMax activation function was used in the fully connected classification layer. The model was evaluated on five public datasets: PlantVillage, Embrapa, Apple, Maize, and Rice, achieving accuracies ranging from 90% to 99%. Specifically, it achieved 99.16% accuracy on PlantVillage and 93.66% on Embrapa.

2.1. Research gap identification and analysis

After conducting a comprehensive and detailed review of the literature discussed above, the following key challenges have been identified and highlighted for exploration and consideration.

2.1.1 Class variation

In agricultural image analysis, class variation is a significant challenge. Intra-class variation refers to differences within the same category or class, such as plants of the same species exhibiting different features like the shape and color of the RoI. Inter-class variation highlights the difficulty of distinguishing between different plant species or diseases that may exhibit similar visual features [19]. These variations make a challenge for machine learning models to classify or detect specific agricultural traits accurately. Addressing class variation require robust feature extraction and classification techniques. To illustrate both these challenges a visual representation is provided in Figure 1 and Figure 2.



Figure 1: Inter-Class Variation a) Grape Black Measles b) Grape Black Rot.



Figure 2: Intra-Class Variation a) Grape Leaf Blight b) Grape Leaf Blight.

2.1.2 Region of interest scale variation

Scale variation refers to changes in the size of RoI in the image caused by different angles and distances of camera while capturing the image [33]. In agriculture, this is particularly problematic for machine learning algorithms as diseases might appear small and distant in one image and large and close-up in another [33]. A visual

representation of the ROI challenge is illustrated in Figure 3.



Figure 3: Region of Interest Scale Variation a) Potato Early Blight at early-stage b) Potato Early Blight at advance stage.

2.2 Research gap

Despite significant progress in using CNNs for plant disease detection, several gaps persist:

1. **Gradients Vanishing in Simple Feed-Forward Models:** Models like VGG16 and AlexNet often struggle with gradients vanishing, causing training difficulties and reducing their ability to learn complex patterns [20]. This limits their effectiveness in handling subtle disease features.
2. **Neglect of Multilevel Features in Inception-Net:** While Inception-based models capture features at multiple scales, they often fail to fully integrate features learned at different depths. This can result in missing important information needed for identifying diseases that vary in appearance across different layers [20].
3. "**Dead Neuron" Phenomenon in Traditional Activation Functions:** Common activation functions like ReLU and Sigmoid can lead to "dead neurons," where some neurons stop responding to any input. This reduces the model's capacity to learn new patterns, ultimately affecting performance [34].

3 Proposed framework

In this section, we provide a comprehensive discussion of the proposed approach, outlining the CNN architecture in detail in the following subsections. Before delving into the specifics, we offer a concise overview to provide readers with a brief understanding.

3.1 Data acquisition

For this study, we utilize the publicly available PlantVillage and the CLD benchmark datasets. These datasets, summarized in Table 1, provide a comprehensive collection of images, enabling the training and evaluation of our proposed model across a diverse range of crops and disease types.

3.1.1 PlantVillage dataset

The PlantVillage dataset is a widely recognized resource for plant disease detection, comprising 18,908 images from various plant species. It offers high-quality, annotated images across multiple classes, facilitating accurate model training and evaluation.

This research focuses on the classification of multiple plants and their associated diseases as shown in Figure 4.

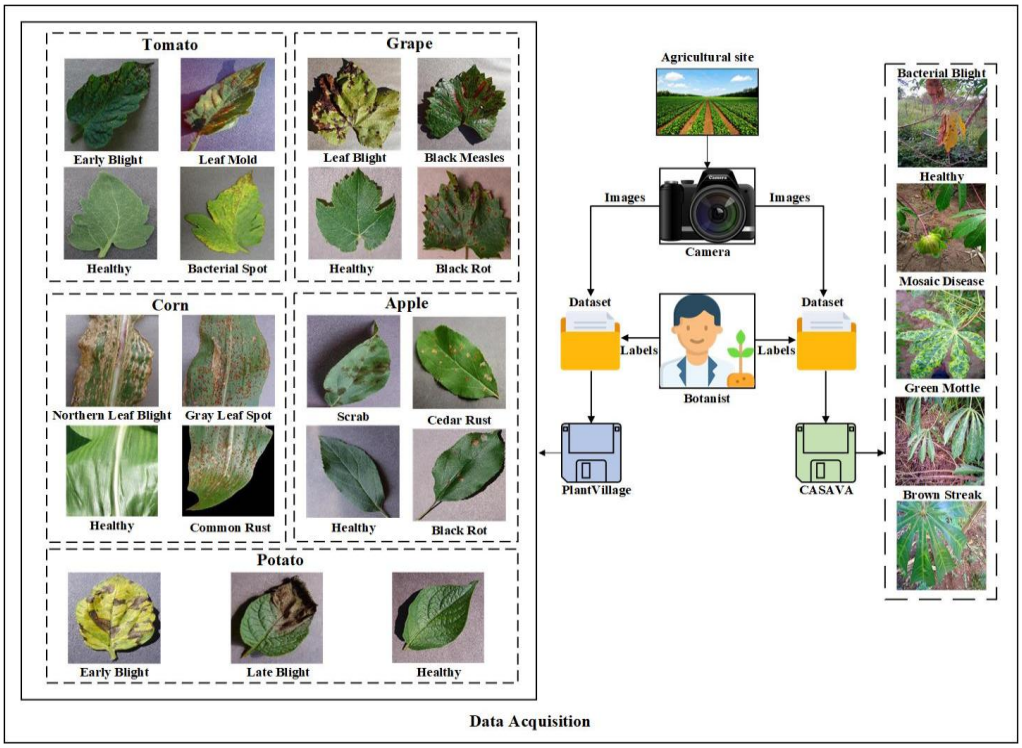


Figure 4: Data preparation.

Table 1: Dataset's description.

Plants	Classes	Image Frequency			
		Train (70%)	Validate (10%)	Test (20%)	Total
Corn	Northern Leaf Blight	689	98	198	985
	Gray Leaf Spot	359	51	103	513
	Healthy	813	116	233	1162
	Common Rust	834	119	239	1192
Apple	Apple Scab	441	63	126	630
	Healthy	1151	164	330	1645
	Apple Rust	192	27	56	275
	Black Rot	434	62	125	621
Grape	Leaf blight	753	107	216	1076
	Black Measles	968	138	277	1387
	Healthy	296	42	85	423
	Black Rot	826	118	236	1180
Potato	Early Blight	700	100	200	1000
	Late Blight	700	100	200	1000
	Healthy	106	15	31	152
Tomato	Healthy	1113	159	319	1588
	Early Blight	700	100	200	1000
	Bacterial Spot	1488	212	427	2127
	Leaf Mold	666	95	191	952
Cassava	Healthy Cassava Leaves	350	50	100	500
	Cassava Bacterial Blight	350	50	100	500
	Cassava Brown Streak	350	50	100	500
	Cassava Mosaic Disease	350	50	100	500
	Healthy	350	50	100	500

For apples, the identified classes comprise of Apple Rust, Black Rot, Apple Scab and Healthy. Corn is classified into Northern Leaf Blight, Gray Leaf Spot, Common Rust, and Healthy samples. Black Rot, Black Measles, Leaf Blight, and Healthy leaves belong to the grape class. Potato diseases are grouped into Late Blight, Early Blight, and Healthy states. Lastly, tomato classes comprise Leaf Mold, Early Blight, Bacterial spot, and Healthy samples. This classification forms the basis of the study, highlighting a diverse range of plants and associated diseases. The PlantVillage dataset provides a different variety of plants, both healthy and diseased, making it compatible for training a multi-class plant disease detection model.

3.1.2 Cassava leaf disease

The CLD dataset focuses on cassava, one of the most crucial staple crops in many developing countries. Cassava leaves are prone to various diseases, significantly impacting crop yield and food security. To evaluate our model on real-world images, we selected 500 images per class from the CLD dataset, total of 2,500 images. This dataset contains five distinct classes, including both healthy and diseased leaf images as shown in Figure 4.

3.2 Preprocessing

Figure 5 explains the process of standardizing image sizes, which ensures consistency in the dataset, reduces computational demands, and improves the model's performance by providing uniform input images. This study employs bicubic interpolation, a method that calculates new pixel values using the weighted sum of 16 neighboring pixels. This technique provides smoother transitions and improved image quality compared to other methods like nearest-neighbor or bilinear interpolation. Additionally, it excels at retaining smooth gradients, further supporting more accurate feature extraction during training.

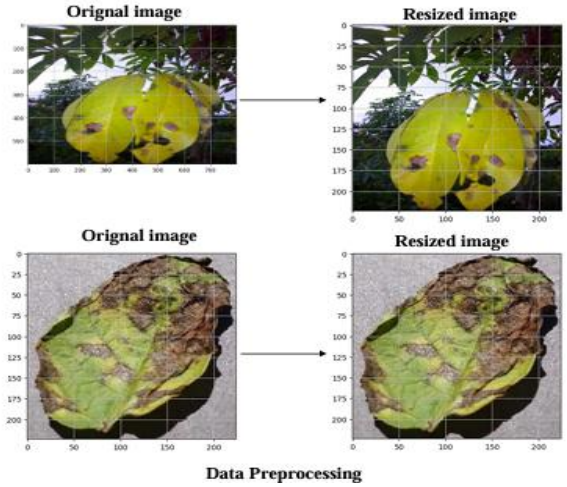


Figure 5: Image resizing.

3.3 HFFIncep-Net for feature extraction and classification

In Figure 6, the proposed HFFIncep-Net architecture, a novel solution designed to overcome the limitations of existing CNNs for multi-class plant disease classification, particularly at early stages. This model integrates hierarchical feature fusion [20] and multiscale feature extraction [35], enhancing its ability to analyze complex

plant disease symptoms with minimal information loss. By combining a robust feature extraction mechanism with advanced architectural enhancements, HFFIncep-Net ensures superior classification performance.

At the core of the architecture is the HFF-Net Stem, which processes 224 × 224-pixel colored input images to extract hierarchical multiscale features. The stem consists of four parallel convolutional layers, each configured to operate at different scales, enabling the model to capture a diverse range of spatial features. The first convolutional layer (conv.1) extracts feature maps (FMs) of dimensions 224 × 224 × 64 using a 3 × 3 filter with a stride (S) of 1, preserving fine details in the image. The second layer (conv.2) reduces the input dimensions, producing 112 × 112 × 64 FMs with a 3 × 3 filter and S = 2, while the third (conv.3) and fourth (conv.4) layers generate 56 × 56 × 32 FMs using 5 × 5 and 7 × 7 filters, respectively, both with S = 4. These multiscale feature maps are fused through a carefully designed hierarchical process to retain critical details while minimizing computational complexity.

The hierarchical fusion mechanism employed in the HFF-Net Stem ensures that features from different scales are effectively combined. The FMs from conv.1 are down sampled using a Max Pooling (MP) layer and concatenated with those from conv.2, producing feature maps of dimensions 112 × 112 × 128. These concatenated FMs are further reduced to 112 × 112 × 64 using a Channel Pooling Layer (CPL), preserving essential feature information while optimizing processing efficiency. The process continues as features from conv.3 and conv.4 are integrated, producing a final stem output of 56 × 56 × 128 feature maps (FMs). This robust feature extraction process mitigates information loss and ensures a rich representation of the input image, optimized for subsequent multiscale analysis [20].

To further enhance the model's capacity for multiscale feature extraction, two Inception V3 blocks are incorporated after the HFF-Net Stem. These blocks process the stem output through multiple convolutional filters of varying dimensions 1 × 1, 3 × 3, and 5 × 5 alongside a Max Pooling operation. The outputs from these filters are concatenated, creating a unified representation that captures patterns at various scales. This approach is particularly effective in addressing the diverse manifestations of plant diseases, which may appear as small spots or large lesions. By leveraging these multiscale feature representations, the Inception blocks significantly enhance the model's ability to distinguish between different disease classes.

The performance of the HFFIncep-Net is further improved through several architectural enhancements. The Swish activation function is employed across the network, offering a smoother gradient flow and improved learning stability compared to traditional activation functions. Batch Normalization is applied in the convolutional layers to standardize feature distributions,

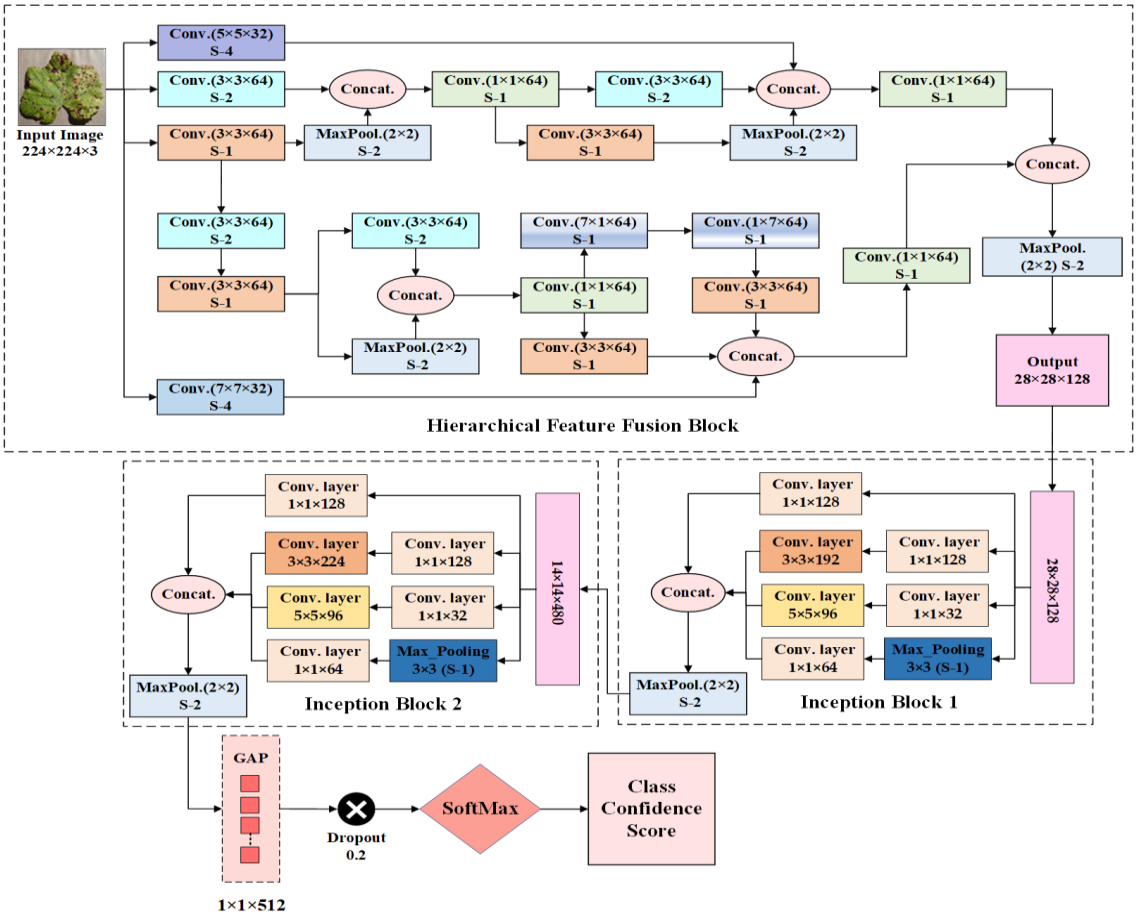


Figure 6: The proposed HFFIncep-Net CNN architecture.

reduce internal covariate shifts, and prevent overfitting. Additionally, a GAP layer is incorporated at the higher levels of the network, aggregating spatial information without the need for fully connected layers. This model not only improves classification accuracy but also reduces the risk of overfitting, ensuring the model's ability to perform effectively on unseen data.

3.4 Activation function

Choosing the right activation function is important for how effectively a model learns and generalizes.

Swish activation function

The Swish activation function is defined as:

$$Sigmoid\ (x) = x * Sigmoid(x) \tag{1}$$

Where $Sigmoid(x)$ is Sigmoid function, and it's given by the equation:

$$Sigmoid\ (x) = \frac{1}{1+e^{-x}} \tag{2}$$

Equation (1) multiplies the input by the sigmoid of the input, creating a smooth curve. This produces negative outputs for negative inputs, which helps avoid the gradient vanishing problem, ensuring gradient flow even for small or negative inputs. These features help the model learn better, keep gradients flowing smoothly, and reduce the chance of neurons becoming "dead" (i.e., stopping learning) [20].

3.5 Loss function

To effectively train the HFFIncep-Net for the plant disease detection, we used the sparse categorical cross entropy loss function. The formula for the loss function is defined in the equation (3):

$$Loss = -\sum_{i=1}^{n} t_i \log\left(p_{i,y_i} \right) \tag{3}$$

Here, L denotes the loss, N indicates the total number of samples, y_i denotes the integer label for the i^{th} sample, and p_{i,y_i} represents the predicted probability that the i^{th} sample belongs to its correct class, represented by y_i.

3.6 Model training and evaluation

In this study, we utilized Google Colab's cloud environment to train and evaluate our HFFIncep-Net for plant disease detection, leveraging the available GPU acceleration. The training setup included a batch size of 32 and was configured for 40 epochs to strike a balance between learning efficiency and model accuracy. We chose the Adam optimizer for its adaptive learning rate capabilities, which helped in effectively facilitating model convergence.

Instead of using model checkpointing, we chose to train the model for the full 40 epochs, ensuring that the final model weights represent comprehensive learning from the entire dataset. This approach provided a robust framework for detecting various plant diseases and optimized the model's performance in accurately classifying plant health across multiple categories.

3.7 Evaluation metrics

In this study, we assessed the model's ability to detect and categorize different plant diseases using performance indicators, such as accuracy, recall, precision, and the F1-score. Formulas for these metrics are as follows:

$$\boldsymbol{Precision} = \frac{TP}{TP+FP} \tag{4}$$

$$\boldsymbol{Recall} = \frac{TP}{TP+FN} \tag{5}$$

$$\boldsymbol{F1-score} = 2 \times \frac{(Recall \times Precision)}{(Recall+Precision)} \tag{6}$$

$$\boldsymbol{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \tag{7}$$

4 Experiment and results

In this study, we tested the HFFIncep-Net model for plant disease detection and compared its performance with several well-known CNN architectures: ResNet-50, Inception V3, DenseNet-201, VGG16, MobileNet, and AlexNet. Each model has its own strengths. ResNet-50 uses residual connections to solve the vanishing gradient problem, helping it learn better as the network gets deeper. Inception V3 captures features at multiple scales, which is useful for recognizing the varied visual patterns in plant diseases. DenseNet-201 improves feature sharing and reduces computation by connecting each layer to every other layer. VGG16, while simple, is effective in extracting features through its deep structure, and AlexNet provides a solid baseline for comparison. MobileNet, designed for lightweight applications, optimizes computational efficiency while maintaining high accuracy, making it suitable for real-time disease detection in resource-constrained environments.

By comparing HFFIncep-Net against these models, we aim to show its advantages in terms of accuracy, scalability, and handling challenging conditions such as in different lighting, a variety of disease classes, and complex backgrounds. The model demonstrates consistently high precision, recall, and F1-scores, indicating its robustness in classifying both healthy and diseased plants across multiple species. Additionally, the model effectively distinguishes between visually similar diseases, minimizing false positives and false negatives. High classification accuracy observed across different plant species highlights the adaptability of HFFIncep-Net to diverse agricultural conditions. The HFFIncep-Net results on different plants are shown in Table 2.

Table 2: The proposed HFFIncep-Net performance.

Benchmark	Class Label	TP	FP	FN	TN	Pr. %	Rec%	F1. Score %
Apple	Apple Rust	55	0	1	587	100.00	100.00	100.00
	Apple Scab	123	2	3	515	99.21	99.21	99.21
	Black Rot	125	1	6	511	100.00	100.00	100.00
	Healthy	329	8	1	305	99.70	99.70	99.70
Corn	Common Rust	239	0	0	534	100.00	100.00	100.00
	Gray Leaf Spot	87	4	16	666	95.60	84.47	89.69
	Northern Leaf Blight	193	16	5	559	92.34	97.47	94.84
	Healthy	233	1	0	539	99.57	100.00	99.78
Grape	Black Measles	277	2	1	535	99.28	99.64	99.46
	Black Rot	235	0	1	579	100.0	99.58	99.78
	Leaf Blight	213	1	3	598	99.53	98.61	99.06
	Healthy	85	2	0	728	97.70	100.0	98.83
Potato	Early Blight	200	0	0	231	100.00	100.00	100.00
	Late Blight	200	1	0	230	99.50	100.00	99.75
	Healthy	30	0	1	400	100.0	96.77	98.36
Tomato	Bacterial Spot	422	1	5	709	99.76	98.83	99.29
	Early Blight	198	5	2	932	97.54	99.00	98.26
	Leaf Mold	190	2	1	944	98.96	99.48	99.22
	Healthy	318	1	1	817	99.69	99.69	99.69
Cassava	Cassava Green Mottle	75	27	25	373	73.53	75.00	72.16
	Cassava Bacterial Blight	88	19	12	381	82.24	88.00	85.02
	Cassava Brown Streak	70	24	30	376	74.47	70.00	72.16
	Cassava Mosaic Disease	84	28	16	372	75.00	84.00	79.25
	Healthy	74	11	26	389	87.06	74.00	80.00

4.1 Proposed model results

4.1.1. Model HFFIncep-Net for Corn

Figure 7 and Figure 8 display the training and validation loss, as well as training and validation accuracy patterns for corn disease classification, providing further insights into the model's performance. The training loss decreases slowly over the epochs and stabilized after the 8th epoch, indicating the model's capacity to acquire features from the training data. The training accuracy respectively increases and stabilizes at a high level.

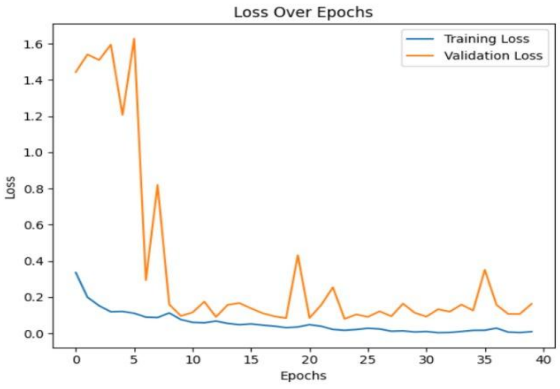


Figure 7: Loss curves of HFFIncep-Net for corn diseases classification.

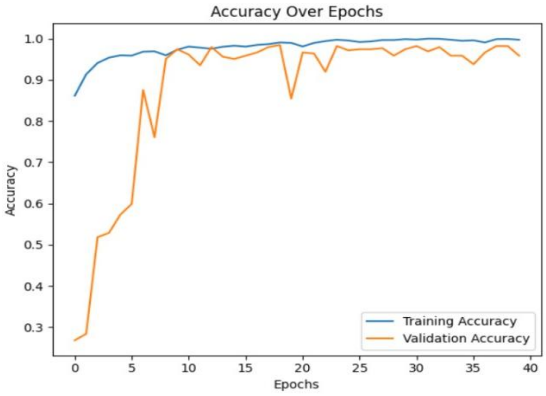


Figure 8: Accuracy curves of HFFIncep-Net for corn diseases classification.

Figure 9 presents the confusion matrix for the HFFIncep-Net in corn disease detection, illustrating the complexity of the classification task, particularly due to significant class variations such as inter- and intra-class differences between Gray Leaf Spot and Northern Leaf Blight. Despite these challenges, the HFFIncep-Net shows impressive performance in identifying various corn diseases.

For Common Rust, the model correctly identified all the 239 samples, proving its strong ability to detect this disease. In the case of Gray Leaf Spot, the HFFIncep-Net accurately classified 87 out of 103 samples, demonstrating its effectiveness in identifying this disease.

The model performed exceptionally well with the more difficult Northern Leaf Blight disease of corn, correctly identifying 193 out of 198 samples, showing it can handle tougher cases. Lastly, for Healthy Corn, the model achieved perfect accuracy by correctly diagnosing all 233 Healthy samples.

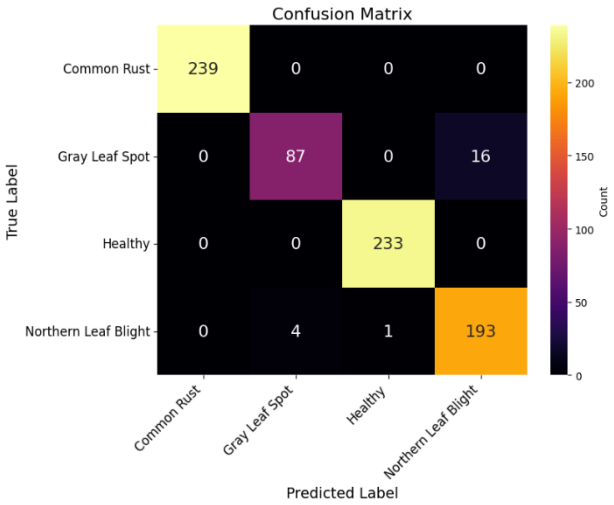


Figure 9: Confusion matrix of HFFIncep-Net for Corn diseases.

4.1.2 Model HFFIncep-Net for Tomato

In Figure 10 and Figure 11, training and validation loss as well as training and validation accuracy plots for tomato disease are presented subsequently that provides further understandings into the model's performance. The validation loss and accuracy stabilized after the 5th epoch, indicating that the model effectively learned features by this point.

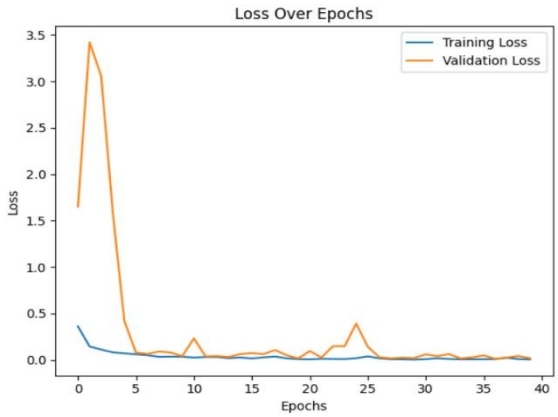


Figure 10: Loss curves of HFFIncep-Net for tomato diseases classification.

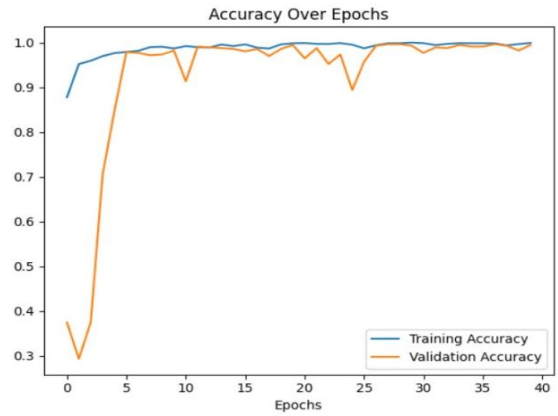


Figure 11: Accuracy curves of HFFIncep-Net for tomato diseases classification.

Figure 12 presents the confusion matrix for the HFFIncep-Net in tomato disease detection, highlights that there is a class variation challenge in bacterial spot and early blight. Although these challenges, the HFFIncep-Net shows impressive performance in identifying various Tomato diseases.

For bacterial spot, the model correctly identified 422 out of 427 samples, proving its strong ability to detect Bacterial Spot disease. In the case of Early Blight, the HFFIncep-Net correctly classified 198 out of 200 samples, establishing its effectiveness in identifying this disease.

The model also performed well with the Leaf Mold disease of Tomato, correctly identifying 190 out of 191

samples just misclassifying one sample, which shows that model is performing accurately in different and complex. Lastly, for Healthy Tomato, the HFFIncep-Net achieved high accuracy, only misclassified 1 sample out of 319 Healthy samples.

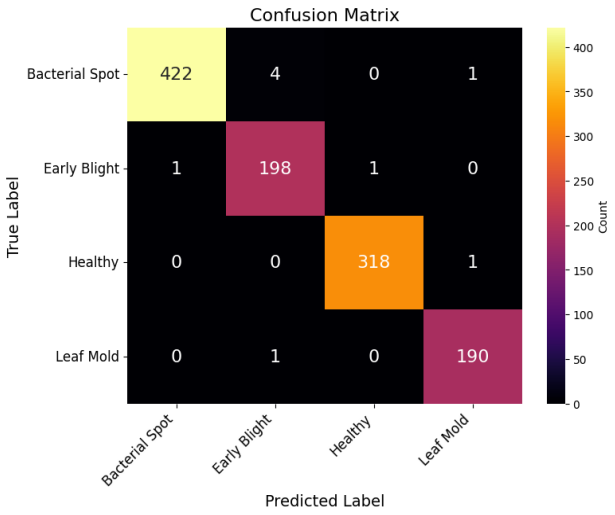


Figure 12: Confusion matrix of HFFIncep-Net for tomato diseases.

4.1.3 Model HFFIncep-Net for Potato

In Figure 13 and Figure 14, which display the training and validation loss as well as training and validation accuracy plots for potato disease subsequently, gives additional insights into the model's performance.

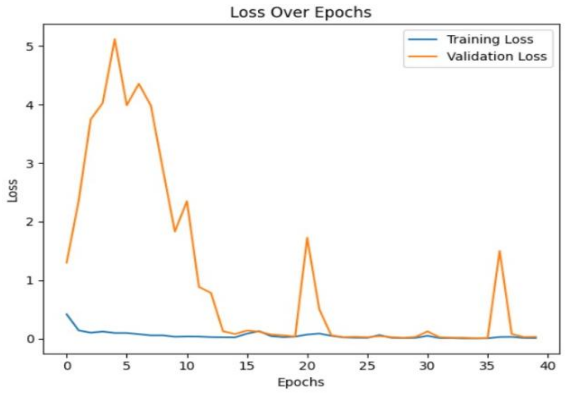


Figure 13: Loss curves of HFFIncep-Net for potato diseases classification.

Figure 15 presents the confusion matrix for the HFFIncep-Net in potato disease detection. The model performs efficiently on all the classes, which shows its strong generalization capability. It correctly distinguishes between Early Blight, Late Blight, and Healthy leaves with minimal error. The model misclassified only one sample across all categories, demonstrating near-perfect performance on potato disease classification. This high accuracy highlights the model's ability to handle subtle visual differences between similar disease classes. Such performance also indicates the model's robustness and reliability in real-world agricultural applications.

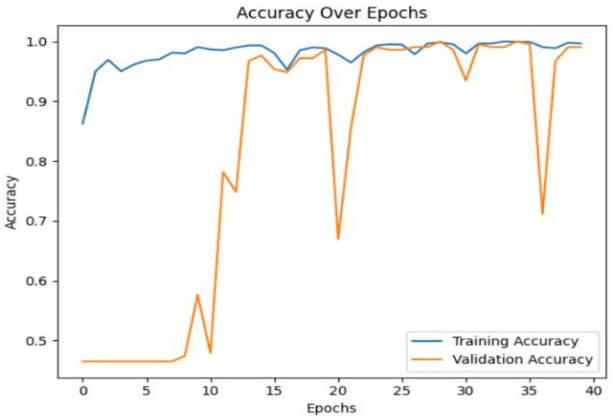


Figure 14: Accuracy curves of HFFIncep-Net for potato diseases classification.

For Early Blight, the model correctly identified all 200 samples. For Healthy, the HFFIncep-Net correctly classified 30 out of 31 samples, and in the case of Late Blight, the model perfectly classified all 200 samples. For Healthy samples, the model misclassified only one sample out of 30. The extremely low misclassification rate demonstrates the model's precision in distinguishing diseased and healthy potato leaves. This further suggests that HFFIncep-Net could be integrated into smart farming systems for automated disease detection and management.

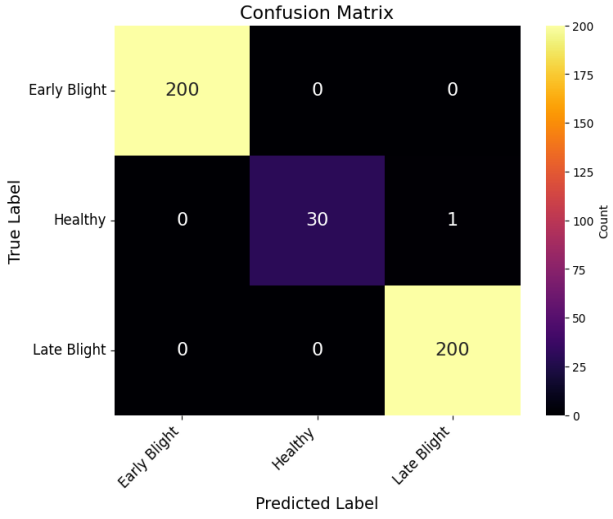


Figure 15: Confusion matrix of HFFIncep-Net for potato diseases.

4.1.4 Model HFFIncep-Net for Grapes

Figure 16 and Figure 17 show the training and validation loss as well as training and validation accuracy plots for grape disease subsequently, which provides further understanding into the model's performance. The validation loss and validation accuracy stabilized after the 7th epoch, which displays efficient model learning ability. This indicates that the model successfully avoids overfitting while maintaining high generalization performance.

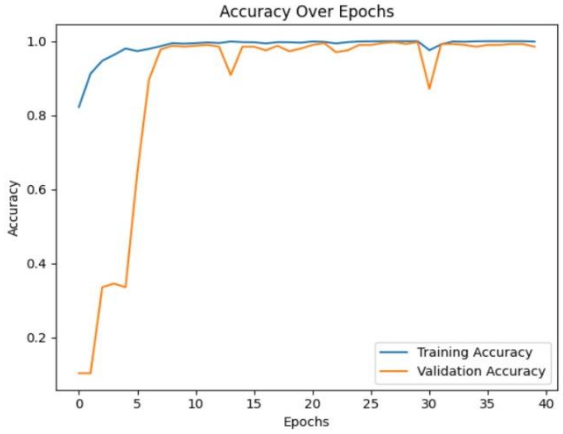


Figure 16: Loss curves of HFFIncep-Net for grapes diseases classification.

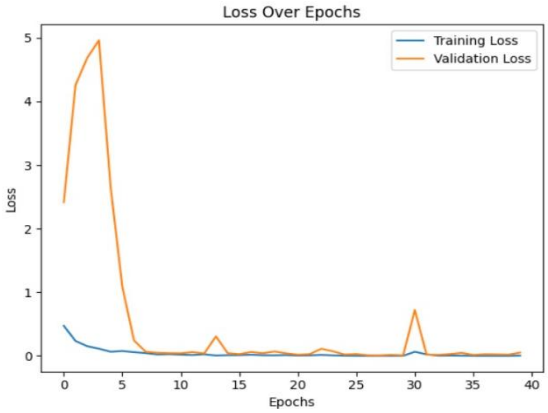


Figure 17: Accuracy curves of HFFIncep-Net for grapes diseases classification.

Figure 18 presents the confusion matrix for the HFFIncep-Net in grape disease detection, highlights that model is performing effectively on all the classes of grapes, and only misclassifies 4 samples. In the case of Black Measles, the model correctly classifies all the 277 samples. And for the case of Grape Black Rot the model misclassifies only 1 sample out of 236 samples.

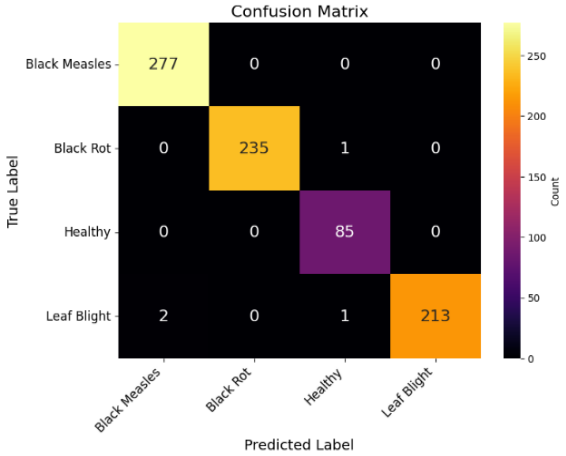


Figure 18: Confusion matrix of HFFIncep-Net for grapes diseases.

For Leaf Blight, the model correctly identified 213 out of 216 samples, proving its strong ability to detect Grape Leaf Blight disease. In the case of healthy grape, the HFFIncep-Net correctly classified all 85 samples which shows valuable model performance.

4.1.5 Model HFFIncep-Net for Apple

Figure 19 and Figure 20 show's how the model performed during training. Figure 19 tracks the training and validation loss, while Figure 20 shows the training and validation accuracy for detecting apple diseases. After the 10^{th} epoch, both the validation loss and accuracy stabilized, meaning the model has learned the important features.

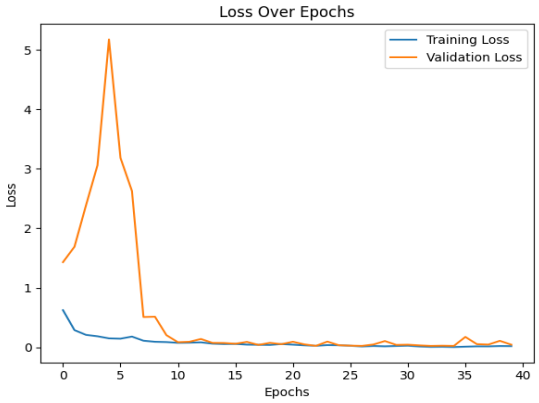


Figure 19: Loss curves of HFFIncep-Net for apple diseases classification.

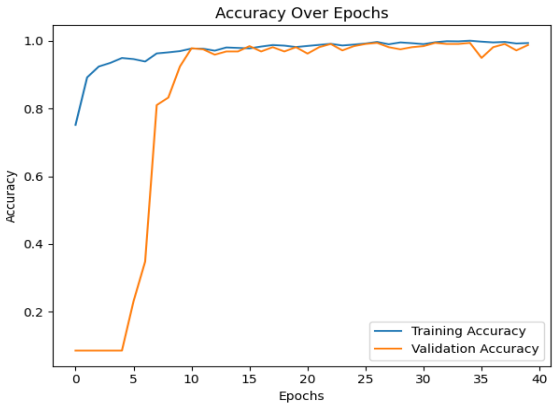


Figure 20: Accuracy curves of HFFIncep-Net for apple diseases classification.

In Figure 21 presents the confusion matrix for the HFFIncep-Net in apple disease detection, highlights that model is performing perfectly on all the categories of Apple, and only misclassifies 2 sample between Healthy and Apple Scab class due to the high-class variation problem. In the case of Apple Rust and Black Rot, the model correctly classifies all the samples, proving its strong ability to detect apple black rot disease And in the case of Apple Scab the model misclassifies only 1 sample out of 125 samples. In the case of healthy Apple, the HFFIncep-Net correctly classified 329 samples and only misclassified 1 sample.

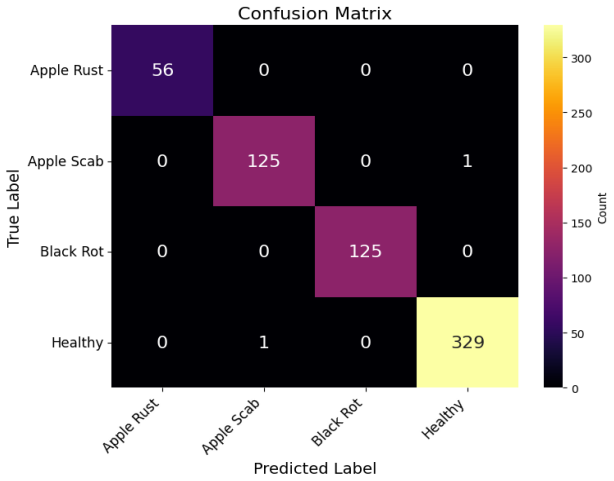


Figure 21: Confusion matrix of HFFIncep-Net for apple diseases.

4.1.6 Model HFFIncep-Net for Cassava

Figure 22 and Figure 23 display the training and validation loss, as well as the training and validation accuracy patterns for Cassava disease classification, providing insights into the model's performance. The training loss gradually decreases over the epochs, while the validation loss also trends downward but exhibits more fluctuations, indicating the model's capacity to learn from the training data. Meanwhile, the training accuracy steadily increases and stabilizes at a high level.

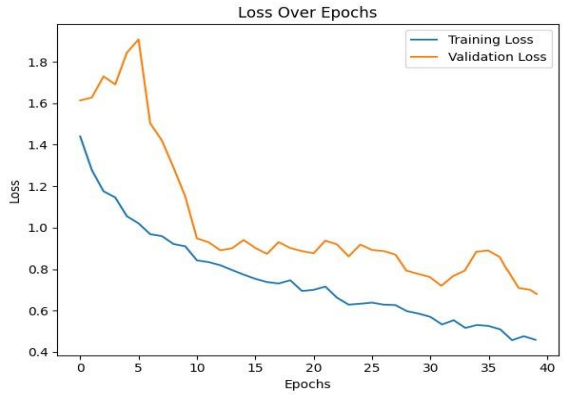


Figure 22: Loss curves of HFFIncep-Net for casava diseases classification.

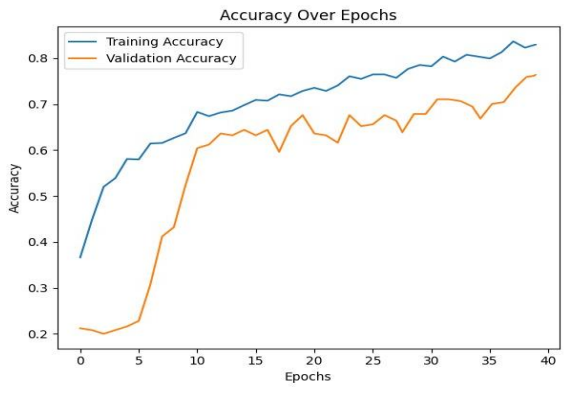


Figure 23: Accuracy curves of HFFIncep-Net for casava diseases classification.

Figure 24 presents the confusion matrix for the HFFIncep-Net in Cassava disease detection, highlighting the model's ability to classify five categories of Cassava leaf conditions. While the model generally performs well, the matrix reveals some misclassifications due to inter- and intra-class variation. The model correctly classifies 88 out of 100 samples for Cassava Bacterial Blight (CBB), demonstrating strong detection of this disease. For Cassava Brown Streak (CBS) case model correctly identifies 70 out of 100 samples, occasionally confusing CBS with CBB. In the case of Cassava Green Mottle (CGM), 75 samples are correctly classified out of 100, indicating moderate confusion with Cassava Mosaic Disease. For Cassava Mosaic Disease (CMD), model accurately classifies 84 out of 100 CMD samples, showing reliable performance on this category. For Healthy Leaves, the model correctly identifies 74 out of 100 samples, with a notable portion misclassified as CGM. Despite these misclassifications, the HFFIncep-Net demonstrates overall strong performance on real-world Cassava images, showcasing its ability to learn discriminative features across multiple disease classes.

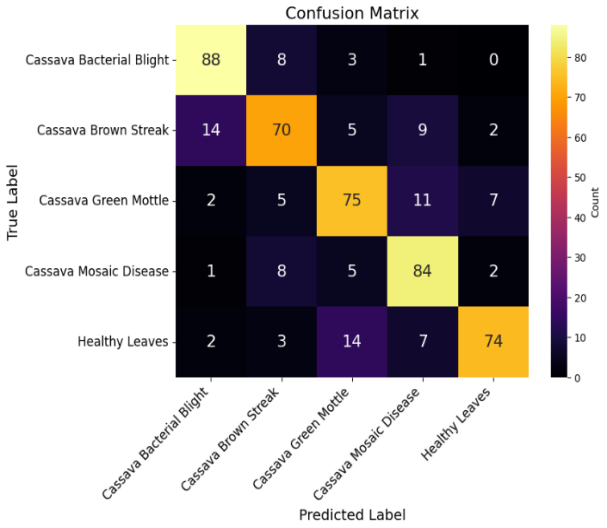


Figure 24: Confusion matrix of HFFIncep-Net for cassava diseases.

4.2 Performance comparative analysis

To evaluate the effectiveness of the proposed HFFIncep-Net, a comprehensive comparison was conducted against several well-established state-of-the-art architectures, focusing on key performance metrics such as precision, recall, F1-score, and accuracy.

MobileNet is significantly lightweight compared to AlexNet, ResNet-50, and DenseNet-201, making it highly efficient for deployment on mobile devices. In terms of performance, MobileNet achieves a precision of 81.04%, a recall of 76.74%, an F1-score of 77.13%, and an accuracy of 90.94%. It provides a strong balance between efficiency and accuracy, making it suitable for real-time applications. AlexNet architecture, which consists of 8 layers in which 5 are convolutional and 3 are fully connected layers. It utilizes 3 × 3 filters with a stride of 1 to capture the features in the image. AlexNet has approximately 61 million parameters and the dropout

layer is used to minimize the risk of overfitting. In the metrics provided, AlexNet achieves a precision of 81.55%, a recall of 78.02%, F1 score of 76.14%, and an accuracy of 90.98%.

ResNet-50 addresses the challenges of training deeper networks by introducing residual blocks with skip connections, effectively handling the gradient vanishing problem and class variation problem (Inter and Intra class variation) by extracting features at multiple levels with different strides. And Resnet-50 has a total of 25 million parameters which means it is lighter than Alexnet and requires less computation. Resnet-50 is preforming effectively than the Alexnet with the precision of 82.08%, recall of 77.76%, F1 score of 78.51%, and accuracy of 91.28%. This improvement is because of multilevel feature extraction which offers better learning and accuracy.

Densely Connected Convolutional Networks (DenseNet) feature a dense connectivity pattern where each layer is connected to other layers, which enhances feature propagation and reuse. This architecture also addresses the class variation and gradient vanishing problem as features are extracted at multiple levels with different strides (s-1, s-2, e.g.) DenseNet-201 achieved a precision of 85.36%, recall of 79.49%, F1 score of 79.31%, and accuracy of 92.16%, outperforming ResNet-50.

PDD-Net is built on the VGG16 architecture, which is known for its straightforward design with 16 layers, including convolutional filters of 3 × 3. By using VGG16 as its base, PDD-Net benefits from strong feature extraction capabilities while keeping the model efficient. The PDD-Net outperforms the other architecture, with a precision of 86.27%, recall of 86.41%, F1 score of 86.29%, and accuracy of 94.59%.

Inception V3 architecture utilizes Inception modules, which perform parallel convolutions and max pooling operations with different filters to extract features at multiple scales that address the RoI problem. The Inception V3 has approximately 23.9 million parameters. Inception V3 focuses on computational efficiency while maintaining high performance. It achieves a precision of 88.22%, a recall of 86.08%, F1 score of 82.21%, and accuracy of 94.74%.

The proposed HFFIncep-Net is designed for plant disease classification, employing multilevel and multiscale feature extraction techniques to avoid problems like RoI scale variation, gradient vanishing, and class variation problem and then flows into a GAP layer, which compresses it into a more manageable size [20]. The proposed model has approximately 1.2 million parameters, making it lightweight than other state-of-the-art architectures. To mitigate overfitting, a dropout layer with a rate of 0.2 is applied before the final classification layer. The proposed model achieves the highest performance across all other architectures, with a precision of 94.61%, recall of 94.31%, F1 score of 94.31%, and accuracy of 97.80%. Table 3 shows the comparison of proposed HFFIncep-Net model with current state-of-the-art classifiers.

5 Conclusions and future work

This study presents the HFFIncep-Net model, designed to address critical challenges in plant disease detection, including variables like RoI scale variations and intra-class variations. This model leverages a combination of advanced feature extraction techniques, and an activation function optimized to mitigate the issue of inactive neurons. As a result, it demonstrates superior accuracy compared to traditional architecture such as VGG16, AlexNet, and conventional Inception-based models. The findings reveal that the hybrid approach effectively captures essential features across varying scales and depths, enabling precise identification of plant diseases even in complex and dynamic real-world environments. This innovation holds significant potential for empowering farmers and agricultural experts to diagnose crop issues swiftly, safeguard yields, and contribute to a stable and secure food supply chain. Future research directions could involve incorporating additional environmental data or experimenting with state-of-the-art attention mechanisms. By continuously enhancing these models, automated plant disease detection can become faster, more reliable, and widely accessible, benefiting farming communities worldwide.

Table 3: Comparative analysis of proposed model with different State-of-the-art CNN Architecture.

Framework	CNN Architecture	Precision %	Recall %	F1 Score %	Accuracy %
[23]	MobileNet [36]	81.04	76.74	77.13	90.94
[21], [29]	AlexNet [37]	81.55	78.02	76.14	90.98
[26]	ResNet-50 [38]	82.08	77.76	78.51	91.28
[22]	DenseNet-201 [39]	85.36	79.49	79.31	92.16
[24], [25],[19], [27], [32]	VGG16 [40]	86.27	86.41	86.29	94.59
[24], [28], [23], [29]	Inception V3 [35]	88.22	86.08	82.21	94.74
Proposed Model	HFFIncep-Net	94.61	94.31	94.31	97.80

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An Improved Gated Graph Neural Network for Sports Tourism Recommendation: User Embedded Representations and Attention Mechanisms

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Keywords: gated unit, user embedded representation, travel recommendation algorithm, attention mechanism

Received: March 5, 2025

In recent years, as the tourism industry rapidly develops, personalized recommendation systems have become an important tool for improving user experience and satisfaction. However, traditional methods face problems such as insufficient recommendation accuracy and low computational efficiency when dealing with large-scale data and complex user needs. Therefore, a sports tourism recommendation model (TRM) based on improved gated graph neural network and user embedded representation is proposed. The model integrates user behavior data and attraction features, and adds attention mechanism and gated unit to improve recommendation accuracy. The dataset used in the study is publicly available on TripAdvisor, which includes detailed user reviews, ratings, and historical behavior data of tourists. The baseline models used for comparison are graph neural networks and attention-based graph neural networks. The performance of this model is evaluated based on several metrics, including F1 score, accuracy, AUC, and inference speed. The research results indicate that the proposed model achieves the highest F1 score of 0.95 after approximately 150 iterations and an accuracy of 0.98 after approximately 100 iterations. Moreover, the model performs outstandingly in terms of recommendation accuracy, relevance, and computational efficiency, with an AUC value of 0.97, inference speed of 0.02 seconds, and computation time of 45 seconds. The findings denote that the proposed model effectively improves the personalization and computational efficiency of tourism recommendations, and can provide users with more accurate recommendations of tourist attractions.

Povzetek: Prispevek predstavi izboljšan model Gated Graph Neural Network z uporabniškimi vdelanimi predstavitvami in mehanizmom pozornosti za natančnejše priporočanje turističnih destinacij v športnem turizmu.

1 Introduction

With the rapid development of the tourism industry, personalized recommendation systems have gradually become an important tool for improving user experience and enhancing user satisfaction. Traditional tourism recommendation methods often rely on rule-based recommendation systems or simple content-based recommendation methods, which often cannot effectively handle users' complex needs and diverse preferences. Therefore, data-driven personalized recommendation systems have become a hot research topic [1-2]. In recent years, as the machine learning and deep learning technologies advance, graph neural networks (GNNs) have achieved significant results in the application of recommendation systems. GNN can effectively capture the relationships between attractions by processing graph structured data, and extract potential patterns between users and attractions through node aggregation operations. However, existing GNN methods still have some limitations in practical applications, especially when dealing with the temporal nature of user behavior and complex relationships between attractions, which often perform inadequately. Therefore, a sports TRM based on improved gated graph neural network (GGNN) and user embedded representation is proposed. This model improves the GNN model by introducing attention mechanisms (AM) and gated units, enabling the model to fully utilize user behavior data and enhance its computational efficiency and recommendation accuracy. Introducing user embedding representation in personalized recommendation systems can significantly improve the accuracy of recommendations, as it can better capture users' personalized features and preferences. However, this process also brings some computational trade-offs. User embedding representation requires additional parameters to represent the behavior and preferences of each user. This means that during the training process, the model needs to store and update a large number of embedding vectors. As the number of users increases, the demand for storage and computing will also sharply rise, leading to an increase in training time. Embedded representation is usually a high-

dimensional vector, and each user has an embedded vector. This leads to significant memory consumption, especially on large-scale datasets. As the size of the dataset expands, storing embedded representations for each user will consume a significant amount of memory space, further increasing hardware requirements. The research aims to provide a more accurate and efficient tourism recommendation system, and provide new ideas for the field of personalized recommendation research. The main research questions include: 1) How can the GGNN model outperform traditional GNN and AGNN models in recommendation accuracy by introducing user embedding representation and AMs. 2) Is there a trade-off in the computational efficiency of GGNN while improving recommendation accuracy. 3) How does this model handle the cold start problem and can it maintain good recommendation performance in situations where data is scarce for new users or new attractions. The main contributions of the research include: proposing a TRM based on improved GGNN, which combines gate units and AM, significantly improving recommendation accuracy and computational efficiency. By introducing user embedding representation and attraction embedding representation, the model can capture users' interests and attraction features more personalized, overcoming the shortcomings of traditional methods in big data and dynamic user needs. An innovative time series modeling method has been proposed to enable recommendation systems to consider the dynamic changes in user preferences, thereby improving the real-time and accuracy of recommendations. The research is mainly divided into five sections. The first section reviews research in related fields, and the second section provides a detailed description of the proposed model structure, including improvements to GGNN, learning methods for user and attraction embeddings, introduction of gating units and AMs, etc. The third section presents the experimental setup and results, comparing the performance of this model with other benchmark models. The fourth section analyzes the advantages, limitations, and future improvement directions of the model. The fifth section summarizes the work of this article and proposes possible directions for future research. The innovation of the research lies in combining user embedded representations with scenic spot features, using gating mechanisms to dynamically adjust the data flow, to better capture the relationship between user preferences and scenic spots.

2 Related works

With the rapid development of the tourism industry, personalized recommendation systems have become an important tool for improving user experience and satisfaction. However, traditional recommendation methods still face problems such as insufficient recommendation accuracy and low computational efficiency when dealing with large-scale data and complex user needs. Rabiu I et al. developed an emotion rating model grounded on long short-term neural networks to address the problems of sparse and imbalanced historical rating data in recommendation systems. This model combined functions to capture emotional biases between user ratings and comments. The research findings indicated that the model could effectively solve the above problems and demonstrated good recommendation performance [3]. Yang Z et al. proposed a method that utilizes unlabeled sample information and location information to raise the accuracy of recommendation algorithms, to address the problem of discarding useful information from unknown entries in the rating matrix in traditional recommendation methods. Meanwhile, to reduce computational complexity, the research team also designed an approximate solution model. The research findings indicated that the method had good predictive performance and exhibited robustness to the diversity of the dataset [4]. Zare A et al. proposed a recommendation system framework grounded on supply chain interaction to address the lack of research on interpersonal relationships in social networks. The system adopted a hybrid method combining artificial neural networks and fuzzy strategies, aiming to recommend similar users to social network users. The research results indicated that this method had good recommendation performance and could effectively match similar individuals [5].

Mohammadi N et al. found that many people are increasingly using online services to meet their needs, but there are many users who lack professional knowledge and cannot express their needs well. The current recommendation system only supports users with precise expression ability. In response to this issue, the research team proposed a powerful recommendation system to meet the demands of various users. The system was capable of collecting user preference information and making information recommendations based on various types of information. The research results indicated that the method model had good effect in both accuracy and scalability, and the accuracy of the model was higher when the dataset capacity was large [6]. Benabbes K et al. believed that as the amount of online information continued to increase, it has exceeded the scope of human processing and effective utilization, resulting in extremely low information utilization rates. A recommendation system can solve this problem. The research team applied existing recommendation models to interpret comment texts for user recommendations. The findings indicated that the model had good performance in interpreting comment texts to obtain user information and make recommendations [7]. Peng B found that although the development of e-commerce has facilitated people, the choice of things can lead to the emergence of information processes, which in turn makes it hard for people to find what they want. In response to this issue, the research team proposed a recommendation system based on fuzzy rough sets and cellular algorithms, which can provide personalized recommendations to users grounded on purchase history, and etc. The results indicated that the recommendation system could provide targeted recommendations to users [8]. Xie X et al. proposed an evaluation model based on snowfall, temperature, and wind speed to enrich the connotation of climate suitability for ice and snow sports and conduct cross regional comparisons. They used meteorological data from 1991 to

2021 to study major ski tourism destinations in China. The results indicated that the overall suitability of different regions has decreased, with significant differentiation and spatial heterogeneity in northern Xinjiang. Snowfall was the main influencing factor [9].

In summary, although recommendation algorithms have been widely applied in multiple fields, existing recommendation system methods have some limitations. Firstly, many traditional rule-based and content-based recommendation methods exhibit poor generalization ability when facing diverse or unfamiliar user behaviors. For example, traditional methods that rely on collaborative filtering cannot effectively provide accurate recommendations for new users or cold start users because they fail to fully utilize users' contextual information. Secondly, many methods fail to effectively capture the temporal characteristics of user behavior. The preferences and behaviors of users change over time, and traditional static models fail to consider this temporal dependence, resulting in a decrease in recommendation performance. Many SOTA methods have low computational efficiency, especially large-scale graph models such as GNN, which require a large amount of computing resources during training and inference. When processing large datasets, there are often computational bottlenecks that cannot meet the needs of real-time applications. Finally, some methods fail to fully focus on learning user embedded representations and lack dynamic adjustments based on user behavior, which leads to recommendation systems failing to accurately capture user preferences. This study proposes a new travel recommendation algorithm by improving GNN and user embedded representation. This model aims to provide personalized tourist attraction recommendations for users by integrating their historical behavior and feature information of attractions, especially for those who have travel needs but have not yet made a clear destination choice. The summary of the above research is shown in Table 1.

Table 1: Summary of model performance indicators

Method	Dataset	Accuracy	F1 score	AUC	Remarks
Rabiu I et al. [3]	Custom Emotion Dataset	0.84	0.71	0.81	Emotion-aware recommendation model
Yang Z et al. [4]	Custom Location Dataset	0.85	0.75	0.80	Combines location info for accuracy
Zare A et al. [5]	Custom Social Dataset	0.89	0.8	0.83	Hybrid ANN & Fuzzy system
Mohammadi N et al. [6]	Custom E-Commerce Dataset	0.90	0.82	0.87	Multi-information recommendation
Benabbes K et al. [7]	Custom Reviews Dataset	0.88	0.79	0.85	Based on text interpretation
Peng B. [8]	E-Commerce Dataset	0.86	0.77	0.81	Fuzzy rough sets & cellular algorithms

3 Sports tourism recommendation

3.1 Tourist attraction recommendation model based on GNN

Tourist attraction recommendation is a service that recommends the most suitable tourist attractions to users grounded on their interests, needs, and preferences through algorithms. Its main purpose is to provide users with personalized and accurate tourist attraction recommendations, helping tourists find the most suitable destination among numerous choices. The tourist attraction recommendation model is shown in Figure 1.

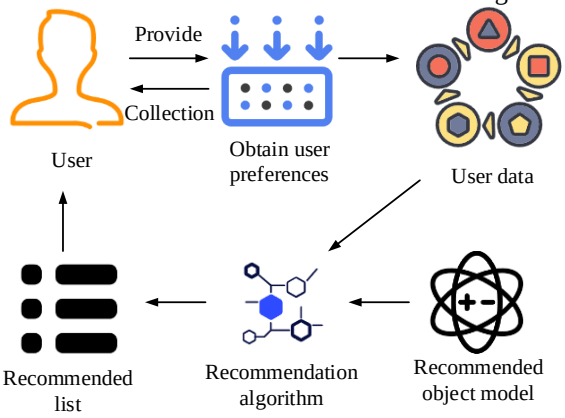


Figure 1: Structure of tourist attraction recommendation model

As shown in Figure 1, the user first provides personal preference data, and the recommendation system obtains the user's preference information based on this data. After obtaining user preferences, the system processes them using recommendation algorithms and generates recommendation results. Subsequently, these recommendation results will be conveyed to the users and further adjustments will be made based on their feedback. Throughout the process, the recommendation system continuously optimizes its recommendation strategy by collecting user preferences and feedback, forming a dynamic adjustment loop to achieve personalized recommendations. The key modules of recommendation methods, user preference models (UPMs), and recommendation result models work together to ensure that the recommendation system can provide users with accurate personalized recommendation services [10]. Through this iterative mechanism, the system can not only satisfy the diverse requirements of users, but also continuously optimize recommendation accuracy and improve user experience. In GNN, each node corresponds to a tourist attraction, and the edges between nodes represent the correlations or relationships between these attractions, such as shared features or user preferences that connect them. In each convolutional layer, nodes aggregate information from their neighboring nodes to update their representations. The expression for feature aggregation is denoted in equation (1).

$$\mathbf{h}_v^{(l+1)} = \sigma\left(\sum_{u\in \mathrm{N}(v)} \frac{1}{c_{vu}} \mathbf{W}^{(l)}\mathbf{h}_u^{(l)} + \mathbf{b}^{(l)}\right) \quad (1)$$

In equation (1), $N(v)$ represents the set of neighboring nodes of node v. c_{vu} is defined as the normalization factor, which is employed to compensate for the discrepancy in the number of neighbours associated with each node. This is achieved by normalizing the information from proximate nodes,

thereby ensuring that the influence of each neighbouring node is appropriately balanced. This factor can be defined as the reciprocal of the degree of a node, ensuring that the influence of each neighboring node on the target node is fairly considered. $\mathbf{W}^{(l)}$ means the weight matrix of the l th layer, $\sigma(\cdot)$ means the activation function, and $\mathbf{b}^{(l)}$ means the bias term. The features of neighboring nodes are aggregated into the target node to enhance its contextual information. After feature aggregation, the representation of nodes is updated through the output of the previous layer, as denoted in equation (2) [11].

$$\mathbf{h}_v^{(l+1)} = \mathbf{h}_v^{(l)} + \mathbf{h}_v^{(l+1)} \tag{2}$$

In equation (2), $\mathbf{h}_v^{(l)}$ and $\mathbf{h}_v^{(l+1)}$ represent the node representations before and after the update, respectively. By integrating information from the previous and current layers, it can better capture the complex features of nodes [12-13]. However, simply calculating the similarity between attractions is not enough to generate user recommendations. In the actual recommendation process, the user's preference information is combined with the similarity between tourist attractions. Firstly, the embedded representation of the user will be subjected to similarity calculation with the representations of various attractions to obtain the matching degree between each user and the attractions. Then, by calculating the recommendation score for each attraction, the user's level of interest in the attraction and the similarity between the attractions are considered. The similarity of scenic spots is measured by calculating the inner product between node representations, as expressed in equation (3).

$$\sin(v,u) = \frac{\mathbf{h}_v^{(L)} \cdot \mathbf{h}_u^{(L)}}{\| \mathbf{h}_v^{(L)} \| \| \mathbf{h}_u^{(L)} \|} \tag{3}$$

In equation (3), L denotes the final layer of the GNN, and $\text{sim}(v,u)$ represents the similarity between attraction v and attraction u. Similar tourist attractions are recommended to users by calculating the similarity between attractions. Finally, based on the calculated similarity, the most matching attraction is recommended to the user, as expressed in equation (4).

$$\hat{r}_{uv} = \sum_{u \in \mathrm{M}(v)} \mathbf{h}_u^{(L)} \cdot \sin(v,u) \tag{4}$$

In equation (4), $\hat{r}_{uv}$ represents the recommended rating of attraction v to users, and $\mathrm{M}(v)$ represents all attractions similar to attraction v. By calculating the recommendation score for each attraction, personalized recommendation lists can be generated for users. GNN uses fixed weights to weight and aggregate information from neighboring nodes, which ignores the differences in information contribution between neighboring nodes. In fact, the impact of different neighboring nodes on the target node is different. Some neighboring nodes may provide more effective information, while others may be noise [14-15]. Therefore, introducing AM can help the model focus more on important neighbor nodes when aggregating neighbor node information, automatically assigning a weight to each edge, thereby improving the model's expressive power. The structure of the introduced AM is denoted in Figure 2.

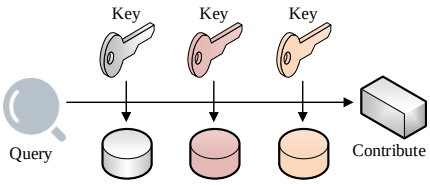


Figure 2: Attention mechanism structure

In Figure 2, the AM is applied within the GNN model to help the system focus on important neighboring attractions during the feature aggregation. The query represents the user's preferences or behavior data, which is used to determine which attractions are more relevant to the user's interests. The keys correspond to the feature representations of the attractions (e.g., location, type, user ratings), while the values represent the attributes or ratings associated with each attraction. The AM calculates the relevance between the query (user's preferences) and the keys (attraction features), assigning higher weights to more relevant attractions. This allows the model to prioritize and aggregate more important features from the neighboring attractions, enhancing the accuracy of the recommendation. The optimized model structure is denoted in Figure 3.

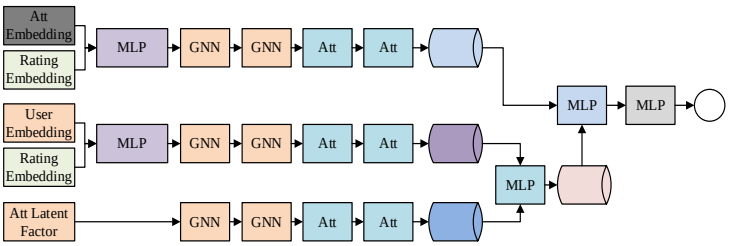


Figure 3: Structure of AGNN model

In Figure 3, the model contains two main modules, namely the UPM and the attraction feature model. In the UPM, the embedded representation of the user is processed together with the rating embedded through a multi-layer perceptron to generate the user's preference information. Then, this information is concatenated with the embedded of scenic spots and potential factors of scenic spots, and input into a multi-layer perceptron to further generate rating predictions. The scenic spot feature model includes multiple attention networks and GNN layers, which are used to process the feature information and graph structure information of scenic spots, respectively, and capture the correlations between scenic spots through AMs and GNN [16]. Finally, through multiple layers of perceptron, the outputs of the UPM and the attraction feature model are combined to generate the final rating prediction.

3.2 Tourism recommendation algorithm based on improved GGNN and user embedded representation

Although the proposed TRM based on GNN can complete most recommendation tasks, the user click sequence is temporal, so inaccurate recommendations may also occur. A TRM based on an improved GGNN and user embedded representation is proposed [17-18]. This model is inspired by recurrent neural network (RNN), which adds gated units to GNN. The time unfolding structure of RNN is shown in Figure 4.

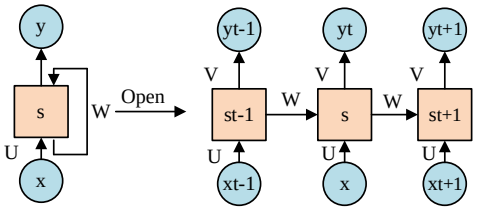


Figure 4: Time evolution of RNN model

In Figure 4, each block represents a moment in the neural network where the input, state, and output of the network interact with each other. At a certain moment, the input value is weighted and inputted into the current state, and the output is calculated through a neural network. Subsequently, the state vector will be passed on to the next moment, and together with the new input, a new state and output will be calculated. This process iterates continuously in time-series data until all time steps are processed, allowing the RNN to capture temporal dependencies when processing sequential data. In this study, the improved GGNN model proposed was inspired by the time series modeling ability of RNNs. However, unlike traditional RNNs, GGNN combines the characteristics of GNNs, especially in each time step, the model not only propagated information through sequence data, but also controlled the information flow in the graph structure through gating units. The introduction of gate control units enabled the model to selectively update node states, retained key memories of user preferences and attraction features, while eliminating noise information. Each node in the graph was embedded with a representation based on its historical behavior and features, and dynamically updated at each time step through the gating mechanism in the GNN. This is similar to the time unfolding structure of RNN, but in GNNs, the state of nodes not only depends on their history, but is also influenced by neighboring node information. On the basis of introducing gated units, the embedding is obtained through projection [19-20]. The structure of the model is denoted in Figure 5.

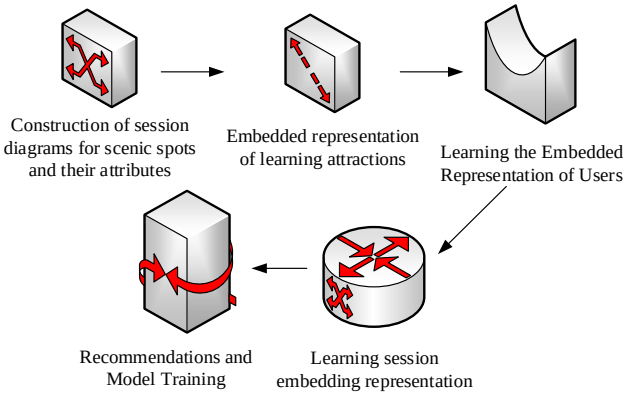


Figure 5: Framework of the proposed GGNN-based recommendation model

As shown in Figure 5, the five key stages of the recommendation process include the construction of a conversation graph of attractions and attributes, learning of attraction embedding representations, learning of user embedding representations, learning of conversation embeddings, and the final recommendation and model training process. Firstly, constructing a conversation graph of scenic spots and their attributes mainly involves building structured data about each scenic spot and its characteristics. Next, by learning the attraction embedded representation module, the system converts the attributes of the attraction into embedded vectors, allowing the representation of the attraction to be manipulated in low dimensional space [19, 21]. Its expression is shown in equation (5).

$$v_s^t = [x_s^t, 0] \tag{5}$$

In equation (5), $v_{s,i}^t$ is the embedded representation of the s th attraction at time t. $x_{s,i}^t$ is the original input feature of the attraction at time t. At the initial stage of the model, the embedding vector of the scenic spot has no historical information. This zero initialization process is the first step in the model learning process. Over time, by combining GNN and attraction attributes, the embedded representation of attractions will gradually update, capturing the features of attractions and user preferences. The expression for attention score is shown in equation (6).

$$a_{s,i}^t = A_s \cdot [v_{s,i}^{t-1}, \ldots, v_{s,i}^0]^T H + b \tag{6}$$

In equation (6), $a_{s,i}^t$ represents the attention score of the s th attraction at time t, which is calculated based on the weight matrix of the attraction and the concatenation of embedded representations from previous time steps.

A_s represents the weight matrix of attraction s, $[v_{s,i}^{t-1},\ldots,v_{s,i}^{0}]$ is the embedding representation, which represents the embedding history of the s th attraction in the past l time steps. These embedding representations capture the temporal changes of attraction features. H is the hidden state, and b is the bias term. The equation for updating the door is denoted in equation (7).

$$r_{s,i}^{t}=\tanh(W_r a_{s,i}^{t}+U_r v_{s,i}^{t-1}) \quad (7)$$

In equation (7), $r_{s,i}^{t}$ is the update gate of the scenic spot s at time t, W_r and U_r are the learned weight matrices, $a_{s,i}^{t}$ is the attention score of the scenic spot, and $v_{s,i}^{t-1}$ is the embedded representation of the previous time [22]. Then, the system enters the stage of learning user embedded representations. In this process, the system will learn the user's embedded vector based on their behavior data, capturing their interests and preferences. The control mechanism enables the embedded representation of scenic spots to be flexibly adjusted according to changes in user behavior, rather than relying solely on the static structure of the graph. This improvement enables the model to capture temporal dependencies, that is, changes in user interest in scenic spots, and provide more personalized and accurate recommendations. Among them, the initial embedded representation of the user is shown in equation (8).

$$h_i^0=(W\cdot \text{Aggreneighbors}(x_k\in N(i)))+b \quad (8)$$

In equation (8), h_i^0 is the initial embedded representation of user i, W is the learned weight matrix, $\text{Aggreneighbors}(x_k\in N(i))$ means the feature vector set of attractions adjacent to user i, and b is the bias term. Specifically, it includes the historical behavior of users and attractions, such as clicks, visits, ratings, etc. These behaviors reflect users' interests and preferences for scenic spots. The attention score is shown in equation (9).

$$y_{ij}^{k}=W_r^2\cdot[x_i \square x_k \square \Phi_k]+b_1+b_2 \quad (9)$$

In equation (9), y_{ij}^{k} represents the attention score of attraction k to user i, W_r^2 is the learned weight matrix, x_i denotes the embedded vector of user i, x_k denotes the embedded vector of attraction k, Φ_k is an additional feature representing attraction k, which typically includes additional information such as attraction type, location, rating history, and user preferences, and b is the bias term. Next, the learning session embedded representation module will combine the embedded representations of users and attractions to learn the embeddeds for each session, which helps to understand the needs of users in different conversations [23]. Ultimately, these embedded representations are used to generate recommendation results and model training. In this part, the system generates personalized recommendations based on previously learned representations and trains and optimizes the model. In the "User Embedding Learning" and "Scenic Spot Embedding Learning" stages in Figure 5, the user and scenic spot embeddings obtained separately will be used as inputs along with the session embeddings for processing by the user embedding layer and scenic spot embedding layer in Figure 6. The relationship between users and scenic spots is finely modeled through the information propagation mechanism in GNNs. The final model structure diagram is shown in Figure 6.

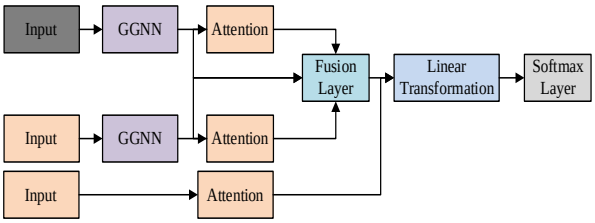


Figure 6: GGNN model architecture diagram

As shown in Figure 6, firstly, the system inputs scenic spot vectors, which are normalized by the Softmax layer to generate probability distributions. Next, these results are connected to vectors from other parts through linear transformation to obtain higher-level feature representations. Then, these input vectors are merged through a fusion layer to generate a comprehensive feature representation that helps the system integrate multiple input information. Next, these data will be input into multiple attention networks, which learn to focus on the important parts of each vector. Next, the system uses a GGNN to update the attraction vector and generate a new representation, while updating the user vector representation through the GNN. Ultimately, through these processed vectors, the system is able to generate personalized recommendation results.

4 Recommendation model performance analysis

4.1 Performance of tourism recommendation algorithm based on improved GGNN and user embedded representation

The study was conducted using a Windows 10 operating system running on a desktop computer with 16G of RAM, an Intel(R) Core(TM) i5-12600KF CPU, and an NVIDIA GeForce RTX 4090D GPU. The study used TripAdvisor's publicly available dataset, which includes travel review data from 500000 users worldwide, covering approximately 10000 tourist attractions. Each attraction was rated on a scale of 1 to 5 based on user feedback. The dataset has high sparsity, with a rating matrix sparsity of 95%, which means that most users did not rate all attractions. Each user comment was accompanied by a timestamp, which records the time of the comment, providing the model with time-series data of user behavior and capturing the temporal changes in user interests. The dataset provided detailed basic information about different

locations, such as the names, locations, and types of attractions, as well as the types of restaurants and hotels. In addition to comments and ratings, the dataset also included users' historical behavior data, such as the attractions visited, pages browsed, and favorite destinations. To ensure the best performance of the model on a given dataset, a grid search method was used to optimize hyperparameters. A comprehensive search was conducted for each important hyperparameter to find the most suitable configuration. The parameter settings of the model are as follows: learning rate was 0.001, optimizer used Adam optimizer (default β 1=0.9 and β 2=0.999), batch size was set to 64, training rounds were 150, L2 regularization weight decay was 0.0005, activation function was ReLU, loss function was cross entropy loss, initial embedding dimension was 128, and gradient clipping was set to a maximum gradient of 5. The study chose GNN and AGNN as the comparison models, and the findings are indicated in Figure 7.

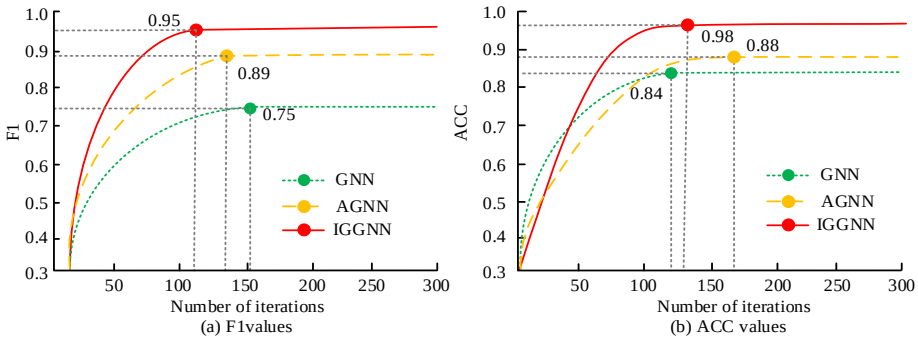


Figure 7: Comparison of F1 and ACC of various models

Figures 7 (a) and 7 (b) show the relationship between the iteration times and F1 score and the relationship between the iteration times and accuracy (ACC), respectively. According to Figure 7 (a), IGGNN reached its highest F1 score of 0.95 after approximately 150 iterations, while AGNN and GNN lagged behind with F1 scores of 0.89 and 0.75. The reason for the superior performance of IGGNN is its more advanced model architecture and more effective regularization techniques, which enable it to better capture important features in tasks. In Figure 7 (b), the IGGNN model performed the best, achieving an ACC of 0.98 after approximately 100 iterations. AGNN and GNN lagged behind with ACC of 0.88 and 0.84, respectively. This model performed well in recommendation ACC, relevance, and computational efficiency, demonstrating more significant advantages than AGNN and GNN. The superiority of IGGNN lied in its more advanced architecture, which effectively combines gating units and AMs. Although AGNN also included these features, IGGNN improved these mechanisms by dynamically adjusting the information flow, allowing the model to focus more on relevant features from past user behavior and suppress irrelevant or outdated data. In addition, the AM in IGGNN helped prioritize the most relevant attractions, ensuring that the model can adapt to changes in user preferences. This dynamic adjustment made IGGNN more advantageous than standard GNN in capturing complex temporal dependencies and generating personalized recommendations. The performance of each model on different types of datasets was analyzed, and the findings are indicated in Figure 8.

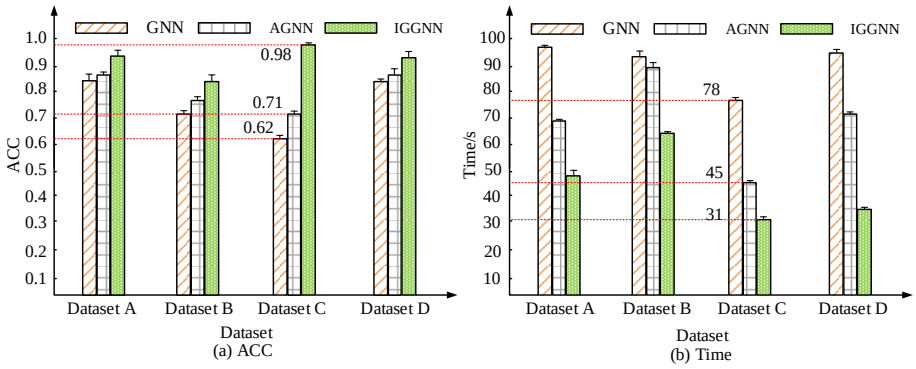


Figure 8: Comparison of ACC and training time of various models on different datasets

Figures 8 (a) and 8 (b) show the ACC and the computation time of three models on different datasets. In Figure 8 (a), the IGGNN model performed the best, with higher ACC than GNN and AGNN on all datasets. On DatasetC, the ACC of IGGNN reached 0.98, significantly better than AGNN's 0.71 and GNN's about 0.62. In

addition, IGGNN also maintained high ACC on DatasetA and DatasetD, outperforming other models. As shown in Figure 8 (b), GNN had the longest computation time, with a computation time of nearly 100 seconds on DatasetA, while AGNN and IGGNN reduced computation times to approximately 70 seconds and 45 seconds, respectively. On DatasetC, IGGNN had the lowest computation time, only 31 seconds, which was significantly reduced compared to GNN. The comprehensive performance of each model was analyzed, and the findings are denoted in Table 2.

Table 2: Comprehensive performance analysis table

Model	IGGNN	AGNN	GNN
F1	0.95	0.89	0.75
ACC	0.98	0.88	0.84
Computing time/s	45	70	100
Iterations	150	120	180
Memory usage /MB	550	500	600
AUC	0.97	0.92	0.85
Inference speed /s	0.02	0.03	0.05

According to Table 2, the F1 score of the IGGNN model was 0.95, with an ACC of 0.98, indicating the best performance. IGGNN significantly outperformed other models in both F1 score and ACC, indicating its clear advantages in capturing important features and improving classification performance. The computation time of IGGNN was 45 seconds, significantly lower than AGNN and GNN, indicating that IGGNN also has higher training efficiency. IGGNN required 150 iterations, while AGNN and GNN required 120 and 180 iterations respectively. Although IGGNN had slightly more iterations, it still dominated in other metrics. The AUC value measured the classification performance of the model at different thresholds. The AUC value of IGGNN was 0.97, which was much higher than AGNN's 0.92 and GNN's 0.85, indicating that IGGNN has significant advantages in overall classification performance. The inference speed of IGGNN was the fastest, only 0.02 seconds, while AGNN and GNN were 0.03 seconds and 0.05 seconds respectively, which means that IGGNN can make predictions more quickly in practical applications. In summary, the IGGNN model performs outstandingly in multiple key indicators, with overall performance superior to AGNN and GNN, especially in terms of classification ACC, computational efficiency, and inference speed. The ablation experiment analysis was conducted on the model, and the results are shown in Table 3.

Table 3: Ablation experiment table

Removed component	F1 score	ACC	AUC	Training time (s)	Inference time (s)
Original GGNN model	0.95	0.98	0.97	45	0.02
Remove gated units	0.9	0.94	0.92	60	0.03
Remove attention mechanism	0.91	0.95	0.93	55	0.02
Remove gated units and attention mechanism	0.85	0.9	0.88	70	0.05

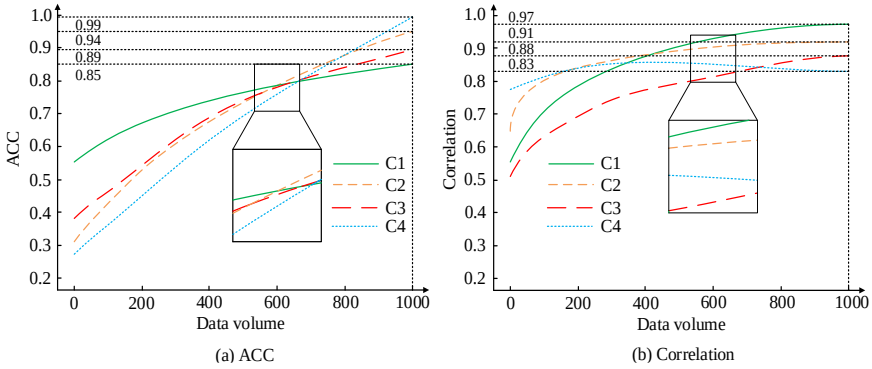
According to Table 3, the original GGNN model showed the highest performance, with an F1 score of 0.95, ACC of 0.98, and AUC of 0.97. When the gating unit was removed, the performance of the model decreased, with F1 score dropping to 0.90, ACC dropping to 0.94, and AUC dropping to 0.92. The training time has also been increased to 60 seconds, indicating that removing the gating unit would affect learning efficiency. The removal of AM could also lead to a decrease in performance, with an F1 score of 0.91 and an AUC of 0.93. Finally, when both the gating unit and AM were removed, the performance of the model significantly decreased, with an F1 score of 0.85, ACC of 0.90, and AUC of 0.88. This indicates that these two components are crucial to the performance of the GGNN model, and their absence can lead to a significant decrease in ACC and effectiveness. The training time has been increased to 70 seconds, which further emphasized the negative impact on learning efficiency when both components were removed.

Compared to AGNN, the GGNN model demonstrated a noticeably faster convergence during training, achieving optimal ACC and F1 score within approximately 100–150 iterations, whereas AGNN required a longer period to reach its peak performance. This trend can be attributed to two main architectural improvements in GGNN: the integration of gated units and user embedded representation. The gated mechanism allowed the model to selectively control the flow of information at each layer, filtering out irrelevant or noisy features and focusing on the most informative inputs. This selective updating process enhanced the model's ability to learn key patterns more efficiently, leading to faster convergence. Additionally, the incorporation of user embedded representations at an early stage gave the model a more expressive initialization of user preferences. As a result, the model could better align user interests with attraction features during the early training phase, accelerating the matching process. In contrast, AGNN lacked the temporal memory and fine-grained control offered by gated units, which results in a slower and more general pattern discovery process. Furthermore, AMs alone, as used in AGNN, were more dependent on large-scale feature interactions to generate meaningful weights, often requiring more training epochs to stabilize.

4.2 Analysis of simulation results of tourism recommendation model

To identify the effect of the model, four different users were chosen for simulation analysis based on their information, and recommended travel destinations that they may be interested in. C1 was an active user with frequent interactions, typically with multiple attractions. The behavior pattern of C2 was relatively clear and stable, but the interaction frequency was slightly lower than C1.

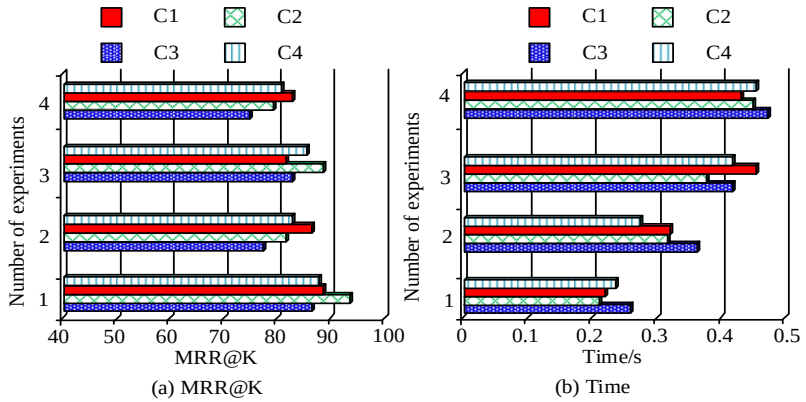
Although the system was able to capture their preferences, less interaction resulted in a relatively slow learning process for the model, especially when the amount of data was small. C3 users had a lower frequency of interaction and exhibited a certain degree of uncertainty or randomness in their behavior. Due to the lack of sufficient behavioral data, the model struggled to accurately capture its preferences, especially in small datasets. C4 was a cold start user with almost no historical behavior data or interaction with attractions. Due to the lack of sufficient interactive information, recommendation systems were unable to effectively provide accurate personalized recommendations, especially when the data volume was small. The results are shown in Figure 9.



(a) ACC (b) Correlation

Figure 9: The recommendation ACC of IGGNN model for different customers

Figure 9 (a) shows the recommendation ACC of the IGGNN model for different customers, and Figure 9 (b) shows the recommendation correlation of the IGGNN model for different customers. in Figure 9 (a), C1 showed an almost linear increase in ACC with the rising of data volume, and the ACC approached 0.95 when the data volume reached 600. In contrast, the performance of C4 was weaker. Despite the increase in data volume, the improvement in ACC was still relatively slow, even reaching only around 0.6 when the data volume was large. However, the overall ACC was above 0.85. From Figure 9 (b), the relevance to C1 rapidly increased when the data volume reached around 500 and stabilized at around 0.97. The relevance performance of C4's recommended content was poor. Although the relevance increased with the increase of data volume, its growth rate was slow and could only reach 0.83 in the end. When the data volume reached 600, the correlation between C2 and C3 stabilized at 0.91 and 0.88, respectively. The findings denoted that the proposed model had excellent recommendation performance. The study selected Mean Reciprocal Ranks (MRR@K) as an indicator. MRR@K measured the location of the scenic spots in the recommended list that best match the user's preferences. The higher the value of MRR@K, the higher the recommended attractions, and the stronger the relevance of the recommendation results to the user. The results are shown in Figure 10.



(a) MRR@K (b) Time

Figure 10: Analysis of MRR@K and recommended time under different experimental times

Figure 10 (a) shows the MRR@K under different experimental times, and Figure 10 (b) shows the recommended time under different experimental times. In Figure 10 (a), for C1, the MRR@K value was significantly higher than other users, staying in the range of 80-90, indicating its efficiency and ACC in recommendation tasks. Relatively speaking, the recommendation performance for C4 was poor, the majority of the MRR@K values were concentrated below 50, for C2 and C3, the MRR@K performance was between C1 and C4. From Figure 10 (b), the time for each recommendation to C4 was the shortest, about 0.2 seconds, indicating that the

C4 model may have high computational efficiency. In contrast, the recommendation time for C1 was the longest, close to 0.4 seconds. The recommendation time of C2 and C3 was between C1 and C4, showing a relatively balanced computational efficiency and ACC. The experimental outcomes showed that the proposed model had excellent effectiveness for all users. The simulation analysis of the model was conducted, and the outcomes are denoted in Table 4.

Table 4: Simulation analysis results of tourism recommendation model

Consumer	ACC	Correlation	MRR@K	Recommended time/s
C1	0.95	0.97	85	0.40
C2	0.9	0.91	78	0.35
C3	0.88	0.88	72	0.31
C4	0.6	0.83	48	0.22
Consumer	The number of experiments	Memory usage/MB	Computing power	/
C1	5	550	0.87	/
C2	5	530	0.83	/
C3	5	540	0.75	/
C4	5	520	0.65	/

In Table 4, computing power represents the CPU/GPU computing power consumed by the model during the training or inference phase, usually indirectly expressed through computation time (in seconds). Higher computing power means that the model requires more time to process data and perform computational tasks. Therefore, computing power is closely related to the running efficiency of the model, which can be measured by the training time and inference time of the model. According to Table 4, C1 had the highest ACC rate, reaching 0.95, indicating the strongest ACC in their recommendation. C4 had a significantly lower ACC rate, only 0.6, indicating poor recommendation performance. The correlation of C1 was 0.97, which performed very well, while the correlation of C4 was 0.83, which was relatively low, indicating that the model failed to effectively capture C4's interests and preferences. C1's MRR@K value was 85, which is greatly higher than other customers, indicating that their recommended results usually rank higher. In contrast, the MRR@K value of C4 was only 48, indicating a low recommendation effect. C4 had the shortest recommendation time, only 0.22 seconds, indicating that its model has high computational efficiency, while C1 had a longer recommendation time, reaching 0.4 seconds. C1 has the strongest computing power at 0.87, performing the best, while C4 had the worst computing power at only 0.65. The findings denoted that the proposed model had excellent performance.

5 Discussion

The IGGNN model proposed in the study significantly outperformed existing GNN and AGNN models in multiple performance metrics, particularly in ACC, F1 score, and AUC value. IGGNN achieved an ACC of 0.98 and an F1 score of 0.95 on the TripAdvisor dataset, while GNN and AGNN performed significantly worse, with accuracies of 0.84 and 0.88, respectively. This improvement can be attributed to the user embedding representation, temporal modeling, and AM introduced in the IGGNN model, which effectively enhance the personalization and ACC of recommendations, and have stronger recommendation performance compared to other methods in existing literature. However, there are also some issues with using IGGNN. Although IGGNN performed well in ACC, its computational complexity was relatively high, especially in the training and inference stages, requiring more computing resources, especially on large datasets, which is similar to the research results of Liu C et al. [24]. Therefore, IGGNN may not be suitable for real-time applications with limited resources. In addition, the interpretability of IGGNN was relatively poor compared to some simple recommendation models. Although AMs were introduced to help the model focus on important features, the complexity of its internal structure still made the decision-making process of the model difficult for users to understand. The performance differences of the model on different datasets were analyzed. IGGNN performed well on the TripAdvisor dataset, but its performance was slightly inferior on other datasets, with an ACC rate dropping to 0.71. This indicated that IGGNN relied heavily on datasets and might not be able to fully utilize its advantages when dealing with datasets with limited data or simple features. Therefore, future research can consider further optimizing the IGGNN model on datasets from different fields to improve its universality. Although IGGNN performs well in most experiments, there are still some limitations. For example, the issue of cold start has not been fully addressed in research. When there is insufficient behavior data for new users or new attractions, the recommendation performance of the model will decrease. Future research can combine transfer learning or reinforcement learning techniques to alleviate this problem. In summary, the IGGNN model proposed in the study has made significant progress in improving recommendation ACC and computational efficiency, but further optimization is still needed in terms of the model's computational efficiency, interpretability, and response to cold start problems.

The IGGNN model proposed in the study has strong deployability in real-world tourism applications. Firstly, the model can process user behavior data in real-time, dynamically adjust recommended content, and ensure the ACC and real-time nature of personalized recommendations. Secondly, IGGNN can support large-scale user and attraction data through efficient computation of embedded representations and GNNs. Although the training phase requires a lot of computing resources, the inference speed is fast and meets real-time recommendation requirements. In addition, the model can provide diversified recommendations to avoid user recommendation fatigue. Finally, the IGGNN model can be regularly updated through incremental learning to maintain continuous performance optimization and adapt to new attractions and changing user needs. In practical deployment, combined with reinforcement learning and

other techniques, the model can continuously optimize itself during the application process, improving recommendation effectiveness.

6 Conclusion

A TRM based on IGGNN and user embedded representation was proposed to solve the challenges of traditional tourism recommendation systems in terms of ACC, timeliness, and computational efficiency. By introducing gated units and AMs, IGGNN could effectively integrate user behavior data and attraction features, significantly improving recommendation ACC and system efficiency. The findings denoted that the IGGNN model performed well in indicators such as F1 score, ACC, and AUC value. The IGGNN model had the best performance with an F1 score of 0.95 and an ACC of 0.98. IGGNN significantly outperformed other models in both F1 score and ACC, indicating its clear advantages in capturing important features and improving classification performance. The computation time of IGGNN was 45 seconds, significantly lower than AGNN and GNN, indicating that IGGNN also had higher training efficiency. IGGNN required 150 iterations, while AGNN and GNN required 120 and 180 iterations respectively. Although IGGNN had slightly more iterations, it still dominated in other metrics. The AUC value measured the classification performance of the model at different thresholds. The AUC value of IGGNN was 0.97, which was much higher than AGNN's 0.92 and GNN's 0.85, indicating that IGGNN has significant advantages in overall classification performance. In the simulation analysis, the ACC of C1 was as high as 0.95, and the recommended time was 0.4 seconds. The outcomes denoted that the proposed model had excellent performance. Although the model performed well in multiple indicators, there were still certain challenges for low-frequency users and cold start problems, especially in situations where the data volume is small or user behavior is low, the recommendation performance of the model may decrease. Future research can further improve the recommendation ACC and generalization ability of the model by combining more contextual information and reinforcement learning techniques.

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YOLO-Based Framework with Temporal Context and Network Analysis for Real-Time Basketball Video Understanding

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Keywords: basketball analytics, YOLO framework, player tracking, passing relationship analysis, network science, sports optimization, deep learning

Received: March 20, 2025

This paper proposes a real-time system for the automated recognition of player interactions in basketball videos using a YOLO-based deep learning framework integrated with temporal context and network analysis. The framework enhances YOLOv3 by incorporating information from adjacent frames to improve jersey number recognition and player tracking under occlusion. A novel algorithm, Joy2019, is introduced to assign consistent player identities over time using retrospective association and temporal smoothing. Passing interactions are represented as directed graphs, and a new Player Centrality (PC) score is developed to evaluate player influence using weighted actions. Experimental evaluation on annotated NBA footage demonstrates that Joy2019 improves jersey number recognition accuracy from 36.1% to 73.8%, and increases player detection rates to 90.2%. Compared to baseline YOLO outputs, the proposed method reduces mean absolute percentage error (MAPE) in pass graph reconstruction to 24.3–33.1%. These findings demonstrate the potential of temporal deep learning and network science to improve the robustness, accuracy, and tactical insight of automated sports analytics systems.

Povzetek: Razvit je nadgrajen YOLOv3 model z začasnim kontekstom in mrežno analizo za samodejno prepoznavo igralcev ter analizo podaj v košarkarskih videih v realnem času.

1 Introduction

Sports analytics is a rapidly changing, interdisciplinary branch of science, which incorporates knowledge in sports science, statistics, mechatronics, electrical engineering, and computer science to develop new solutions to analyze athletic performance and identify the crucial parameters responsible for the success of teams and individuals [1]. In light of the rise of enthusiasm globally towards sports, analytics today is a cornerstone from both professional and amateur points of view, developing very deep methodologies to optimize strategy and performance and understand players. Such team sports like basketball, soccer, and volleyball are the biggest beneficiaries due to these advances through their adoption of analytics strategies and means for improving efficiency and presentation with data-driven insights that go ahead to shape the future management and coaching of teams [2].

In this respect, over the years, the focus of sports analytics has gradually shifted from basic statistical summaries to highly sophisticated computational tools that can unearth intrinsic relationships between players, strategies, and game dynamics. This transformation reflects the higher intricacy of modern-day sports, where data from the on-field action seamlessly integrates with the performance metrics off the field. Tools that were once descriptive analytics have transformed into predictive and prescriptive systems, allowing teams and coaches to take real-world insights into what to do. These days, modern methods mean team behaviors can be looked at on both a macro and micro level for patterns impossible to fathom through human observation. It is this evolution that not only optimizes the potential of every individual athlete but also allows teams to optimize resources and strategies toward overall success [3].

Despite these advances, the field of sports analytics remains very challenging, especially in dynamic team sports where the interaction between players and objects involves complex and continuously changing information. Most traditional methodologies are reliant on human observation in terms of tracking player movements, identifying ball trajectories, or tagging key game events. Such processes are time-consuming, labor-intensive, and easily prone to errors such as false positives and misclassifications [4] [5]. Moreover, this reliance on human judgment comes with inconsistencies that can lead to a lack of reliability in the data and further analysis. This is a crucial bottleneck within the field; hence, there is a dire need for automated systems that can efficiently handle the large volumes of data created during sports events.

The recent emergence of artificial intelligence, especially deep learning, has brought about transformative opportunities in sports analytics [6]. These CNNs and their related frameworks have made object detection and classification applications realistic with near-human accuracy [7]. Among them, the YOLO framework has emerged as the leading real-time object detection system

and has seen wide adoption for various applications in sports analytics. Its ability to process visual data in real time and with high accuracy makes YOLO a very good candidate for player and ball tracking in fast-moving sports. However, the traditional implementations of YOLO are limited in situations where the camera is frequently shifted, players are overlapping, or video sequences are interrupted. These require developing specialized adaptations to fit into special needs in sports analytics.

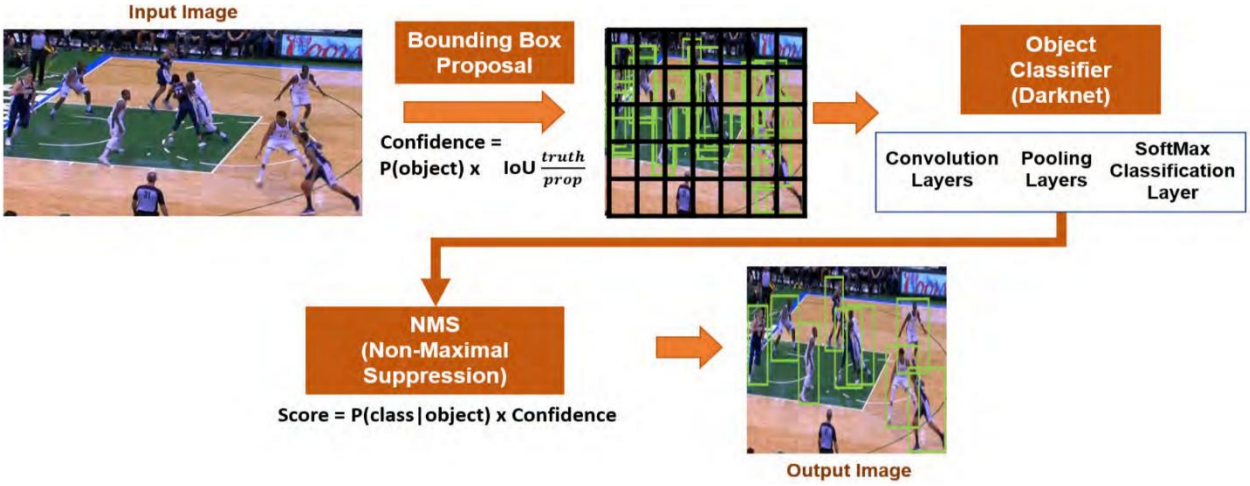


Figure 1: The process of object detection and classification using YOLO.

This paper presents a state-of-the-art system in automatic sports analytics, which leverages the synergy between deep learning and network science to address the above-mentioned challenges. We present an approach that extends YOLO with contextual information from previous and subsequent frames in a video to allow tracking at higher accuracy under adversarial conditions. With this, the system will be able to track players' accurate tracking, jersey number detection, and ball trajectory tracing in very challenging situations. Inspired by network science, we further propose a new metric for the measurement of player importance within the context of team interactions, called Player Centrality. With this, we combine the approaches and provide a comprehensive framework that minimizes manual intervention while giving actionable insights into improving team performance and strategy optimization. The primary objectives of this research are:

(1) To improve jersey number recognition under occlusion by incorporating temporal information from adjacent frames.

(2) To construct and analyze directed passing graphs among players based on ball possession detection.

(3) To propose and evaluate a Player Centrality score that quantitatively reflects player contribution to team dynamics using network science.

2 Related work

Serious research and a number of key developments marked sports analytics as a nascent scientific discipline over the last few decades. Earlier studies mainly related to data aggregation and graphical visualizations of performances via statistical packages contributed a great value to the data insights for game dynamics yet entailed much time-wasting hand-crafting. These efforts mostly focused on summarizing the performance of players and teams, often using simple descriptive statistics that were not deep enough to disclose underlying patterns in player interactions and tactical strategies. Although these studies provided the much-needed impetus to begin with, their reliance on human observation limited scalability and introduced the risk of bias and error [8]. In this phase, much research pointed out that automation approaches can reduce human labor and increase the reliability of sports data analysis.

Deep learning is proving a point of inflection in sports analytics, where tasks are being automated that were till recently at the mercy of a human eye. Among various developments in artificial intelligence, YOLO has emerged as one of the most applied frameworks for object detection and classification in sports analytics. Various studies using YOLO have shown promising results in detecting and tracking players and objects with high precision and speed, even in dynamic and complex environments. However, most of the existing implementations of YOLO exhibit shortcomings when applied to common scenarios featuring heavy camera shifts, occlusions, and overlapping objects. These issues have led researchers to propose enhancements for making the algorithm robust and reliable in sports-specific applications by incorporating contextual information from adjacent video frames [9][10].

On the other hand, network science has emerged as a strong tool in the analysis of team dynamics in sports. By framing player movements and ball passes in network terms, the authors have managed to distill vital information about team strategies and individual contributions. Network science metrics offer systematic centrality measures and clustering coefficients to enable evaluation of player importance and efficiency of team tactics. These methods have been especially successful in team sports like basketball and soccer, where the pattern of passing and positional dynamics often determines the outcome.

Recent works have indeed applied network-based approaches to uncover relationships that were previously hidden by traditional statistical analyses, drawing new perspectives on team performance [11][12].

Other integrated systems also include the integration of sensor data with the video annotation tools and technologies of computer vision for some challenges in sports analytics regarding data collection and processing. The proposed integrated framework of Halvorsen et al. uses sensors and camera systems for automating event tagging and player tracking. While such systems have reduced the need for manual labor, they are still limited by issues of scalability and error management, especially when dealing with large datasets generated in real-time sports environments [13]. These challenges indicate that further approaches are needed to seamlessly handle modern sports data's complexity. A comparison of object detection and tracking methods is shown in Table 1.

Despite the progress made so far, manual event tagging and classification remain significant bottlenecks in the existing sports analytics systems. Numerous studies have proved all these processes to be time-consuming and error-prone, with false positives and false negatives. These constraints make general sports analytics less effective and narrow its capacity to deliver actionable insights. Combined, deep learning and network science drive automated systems around these challenges, with much faster, more reliable solutions that scale. The proposed system further builds on such foundations, providing a holistic framework in the analysis of team sports by fusing YOLO's robustness with network science's analytical power to produce actionable insights that power performance optimization.

Table 1: Comparative summary of related methods for basketball video analysis.

Method	Object Detection	Tracking	Strengths	Weaknesses
YOLOv3 [6] [10]	✓	✗	Fast inference	Fails under occlusion
Faster-RCNN [10]	✓	✗	High accuracy	Low frame rate
Halvorsen et al. [13]	✓ (Sensor-aided)	✓	Multi-modal integration	Needs external hardware
Joy2019 [17]	✓	✓	Temporal robustness, ID reuse	Challenged by long occlusion

3 System design

In this section, we present the mechanism of object detection from video clip frames and a novel machine-learning procedure for recognizing players and their movements.

A) OBJECT DETECTION METHODOLOGY

We adopted the YOLO framework for real-time object detection in basketball video recordings. YOLOv3 has been chosen for its outstanding performance compared to other object detection systems such as Fast-RCNN1 and FasterRCNN2 for the basis of mAP and the speed of object detection measured by Frames Per Second (FPS). Figure 1 presents the mechanism of object detection and classification for YOLO. For every frame of video, YOLO divides the input image into a grid of dimensions $D \times D$. Each cell of that grid proposes multiple bounding boxes and calculates a confidence score for every such box, indicating the likeliness of an object present in that box. The dimension of a bounding box is represnted as (x, y, w, h), where (x, y) represents the center of the box and w, h denotes its width and height. YOLO makes use of a K-means clustering algorithm to create the bounding

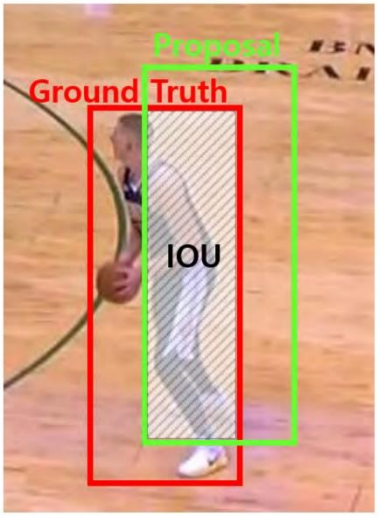


Figure 2*:* An illustration of IOU evaluation.

box dimensions on the basis of training data. The best number of clusters is set to 5; this gives a good balance between computational complexity and high recall [14].

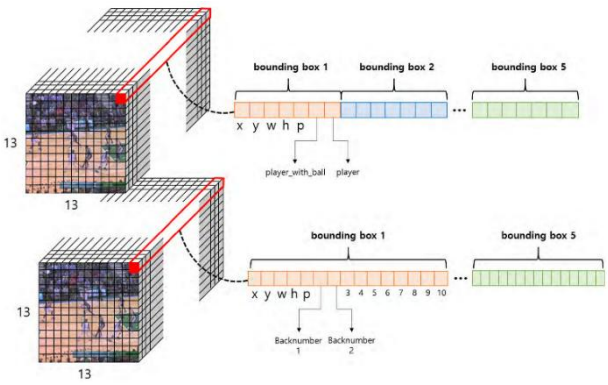


Figure 3: Tensors learned by YOLO for detecting the ball, players, and jersey numbers.

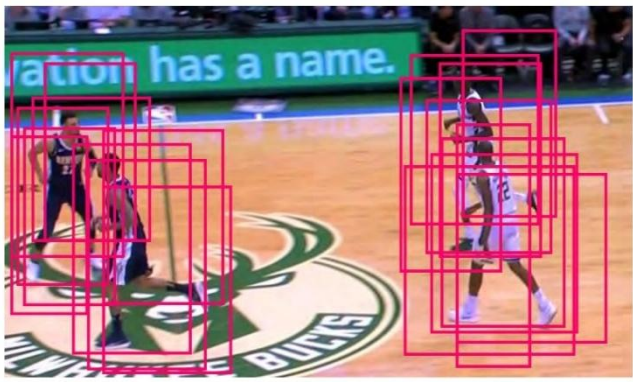


Figure 4: An example showcasing multiple redundant bounding boxes proposed around players.

IoU for each proposed bounding box is calculated between the predicted box and the ground truth box, defined as

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (1)$$

The confidence score for each bounding box, P_{box} , combines the probability of the object being present in the box and its loU with the ground truth box:

$$P_{\text{box}} = P(\text{ Object }) \cdot \text{IoU}_{\text{truth}} \quad (2)$$

Here, P (Object) is the predicted probability that an object is present in the grid cell, and $\text{IoU}_{\text{truth}}$ is the loU calculated between the predicted bounding box and the ground truth bounding box. The final output of YOLO for each cell is represented as a tensor of size $D \times D \times (5B + C)$, where B stands for the number of bounding boxes in each cell, and C stands for classes of objects. For the frames from basketball videos, we set D = 13, which has been found as a sweet-spot resolution allowing good player detection. Each grid cell predicts B = 5 bounding boxes, while the tensor encodes coordinates (x, y, w, h), confidence score, and the probabilities of each class. A two-stage classification process has been introduced to address the challenge of detecting ball possessors and jersey number identification. First, it will detect if a player is a ball possessor or not with C = 2 number of classes. The confidence score for the detection of the ball possessor can be computed as [15]:

$$P(\text{ Ball Possessor }) = \sigma(P_{\text{box}} \cdot P_{\text{class}}) \quad (3)$$

where P_{class} represents the predicted probability of the object being a ball possessor, and σ is the sigmoid activation function that normalizes the output probability. In the second stage, the model identifies jersey numbers for ball possessors. The model will predict C=10 classes corresponding to jersey numbers from 0 to 9. The softmax gives the probability for each class:

$$P(\text{ Class } | \text{ Object }) = \frac{e^{s_i}}{\sum_{j=1}^{C} e^{s_j}} \quad (4)$$

where s_i is the score for class i, and the denominator sums over all class scores. In each grid cell, YOLO uses this probability to assign the detected object to a specific class. This framework is implemented based on Darknet, which is the most optimized C implementation of CNNs to date, allowing real-time performance even for high-resolution frames of basketball videos. YOLO predicts the final score of each proposed bounding box by embedding class probability, object presence probability, and the Intersection over Union (loU) with the ground truth bounding box as presented in Equation 3:

$$P_{\text{box}} = P(\text{ Class } | \text{ Object }) \cdot P(\text{ Object }) \cdot \text{IoU}_{\text{truth}} \quad (5)$$

where P (Class | Object) is the conditional probability of the object to belong to the particular class, P(Object) is the probability of object existence in a grid cell, IoU_„truth „ measures overlap between the predicted bounding box and ground truth box. The obtained combined score allows ranking the bounding boxes for further processing.



Figure 5: Boxes showing the possession of the ball.

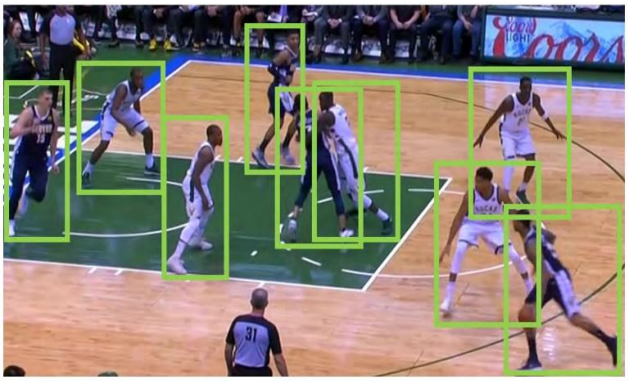


Figure 6: Gathering ground truth bounding boxes for jersey numbers specific to each team.

The grid cells tend to be redundant and generate bounding boxes that are overlapping, especially when multiple cells predict the same object. This is due to the fact that adjacent cells with their fields of view may partially overlap and thus suggest bounding boxes for the same object. Figure 4 illustrates this. In order to overcome this problem, YOLO uses a post-processing method called Non-Maximal Suppression (NMS), which selects and

retains only the most relevant bounding box for every object detected. It then arranges all the predicted bounding boxes in descending order according to their



Figure 7: Gathering ground truth bounding boxes for ball possession detection.

scores, P_{box}. It selects a bounding box that has the maximum score as the most likely candidate for the detected object. For each of the remaining bounding boxes, NMS calculates the loU of that box with the highest-scored bounding box. The box will be discarded if its calculated loU is more than a predefined threshold, $IoU_{\text{threshold}}$. The described process is repeated iteratively until all boxes are processed.

Mathematically, the NMS algorithm can be summarized as follows. Let $\mathcal{B} = \{b_1, b_2, \ldots, b_n\}$ model the set of all proposed bounding boxes sorted by their scores, where b_i is the bounding box with the $i-th$ highest score. For each b_i, NMS retains it if:

$$\text{IoU}\left(b_i, b_j\right) < \text{IoU}_{\text{threshold}}\,,\ \forall j < i \tag{6}$$

Bounding boxes that violate this condition are discarded, as they are considered redundant due to their high overlap with already-selected boxes. It filters such that any single detected object retains only one bounding box, therefore avoiding duplication and enhancing the object detection model as a whole. On the other hand, NMS selects a class for the selected bounding box by considering class probabilities of P (Class | Object), which are derived during the detection stage. By progressive elimination of superfluous bounding boxes, the NMS algorithm seeks to optimize the detection pipeline while delivering dependable bounding box predictions with high confidence for subsequent scrutiny.

B) DEEP LEARNING PROCEDURE

We have collected the ground truth bounding boxes for each class to be recognized by the object detector. For players in possession, the bounding box captured the ball and the torso of the ball possessor, as depicted in Figure 5. For the other players, the whole body was enclosed inside a bounding box, as shown in Figure 6. We also annotated jersey numbers separately by drawing bounding boxes capturing the visible numbers, as shown in Figure 7. Each bounding box was further tagged with team affiliation and the corresponding jersey number to create an extensive dataset for training deep learning models. For recognition, the whole process goes via two stages: recognizing the phase of whether a player has possession of the ball, followed by identifying the jersey number of the player identified carrying the ball. This work actually adopted this two-step method because the capturing of a jersey number for all the players within a frame remains rather challenging and often unresolvable whenever numbers turn out to be blurred out as a result of motion or interaction between the players across differing lighting conditions. A joint approach was not practical since it relies on visibility of jersey numbers across all the frames, which is not always achievable. Limiting data collection only to ball possessors also resulted in an insufficient dataset for training a robust model for recognizing jerseys.

For the first phase, the objective was to classify bounding boxes into ball possessors or non-possessors. This binary classification task required computing the probability $P_{\text{possessor}}$ for each bounding box, defined as:

$$P_{\text{possessor}} = \sigma(P_{\text{box}}) \tag{7}$$

where $P_{\text{box}} = P\,(\text{Class} \mid \text{Object}) \cdot P(\,\text{Object}\,) \cdot \text{IoU}_{\text{truth}}$, as previously established. The training objective for this phase combined binary cross-entropy loss for classification with a regression loss for bounding box coordinates, ensuring accurate localization:

$$\mathcal{L}_{\text{possessor}} = \frac{1}{N}\sum_{i=1}^{N}\Big[-y_i \log P_{\text{possessor}}(x_i) - (1 - y_i)\log\left(1 - P_{\text{possessor}}(x_i)\right)\Big] + \lambda \sum_{i=1}^{N} \text{SmoothL}\ 1\left(b_i, \hat{b}_i\right) \tag{8}$$

Input: Frames: video frames with bounding boxes
Output: LabeledFrames: Frames and their bounding boxes labeled with track IDs and jersey numbers

foreach *frame* $F \in Frames$ **do**
  if F *is the first frame* **then**
    Assign a unique trackingID from 1 to 5 to each bounding box;
    Set F as the preceding frame;
  else
    foreach *bounding box* $c \in F$ **do**
      Find the closest bounding box, b, in the preceding frames;
      c.trackID $\leftarrow$ b.trackID;
      c.jerseyNumber $\leftarrow$ b.jerseyNumber;
      if *the jerseyNumber of c recognized* **then**
        From LabeledFrames, retrieve $P = \{p | p.trackID = c.trackID\}$;
        foreach $p \in P$ **do**
          if *there is no jersey number for p* **then**
            p.jerseyNumber $\leftarrow$ c.jerseyNumber;
      Insert the current frame and its bounding box information to LabeledFrames;

Algorithm 2*:* Joy2019, The Player Tracking Algorithm

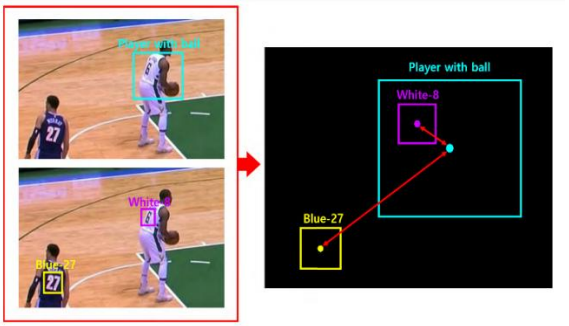


Figure 8: Recognizing the jersey number of the player in ball possession.



Figure 9: An example of associating a jersey number with a box sharing the same tracking ID (tid).

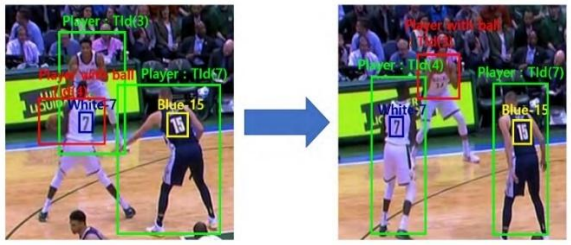


Figure 10: Example of recognizing and tracking pass actions



Figure 11: The challenge of tracking a player box that reappears in the frame.

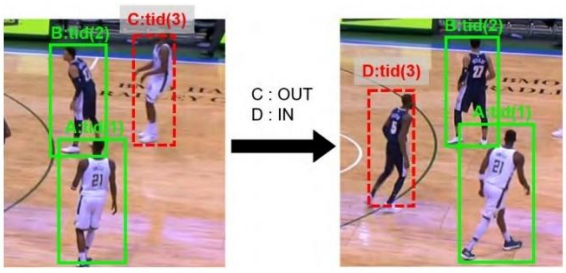


Figure 12: The tracking ID is incorrectly shared between a box that disappeared and a box that reappeared in the scene.

Here, y_i denotes the ground truth label of ball possession, x_i is the input feature of the bounding box, b_i is the predicted bounding box, $\hat{b}_i$ is the ground truth bounding box, and λ is a weighting parameter for the regression term. The second phase of the model focuses on jersey number recognition for the detected ball possessor, involving multi-class classification that calculates a probability distribution over C classes of jersey numbers using the softmax function. The loss fun ction for this phase was the categorical cross-entropy loss, defined as:

$$\mathcal{L}_{\text{jersey}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log P_{\text{class}}(j) \qquad (9)$$

where y_{ij} is a binary indicator (1 if the ground truth class for the sample i is j, 0 otherwise), and $P_{\text{class}}(j)$ is the predicted probability for class j. Extensive augmentation, such as random cropping, flipping, rotation, and adjusting brightness, was used to generate a large-scale training dataset. Those augmented data mimic real conditions where there may be large variations in camera angles of view, partial occlusion, and changing lighting conditions. Outputs of the first-phase ball possessor model were used as the input to the second-phase jersey number model; hence, this became a tightly integrated pipeline for successive detection and recognition tasks [16].

B) DEEP LEARNING PROCEDURE

To track the ball's movement and interaction between players, players and their positions in successive video frames must be identified. Traditional YOLO implementation is limited in handling transitions of scenes and overlapping players in two-dimensional video frames due to the loss of absolute coordinate information. However, YOLO cannot recover the track of players and balls once they are lost temporarily due to a camera angle change or occlusion. In view of such challenges, we adapted YOLO and developed a new tracking algorithm called Joy2019, which increases reliability and accuracy in tracking under even complex situations. For any given frame, Joy2019 [17] assigns a unique tracking ID (tid) to each detected player box using the algorithm. For example, as can be seen from Figure 8, jersey numbers are not directly labeled on player boxes unless the back number is clearly visible. If a new player box is detected, the algorithm searches up to ten preceding frames to find a matching box with the same tid within the closest proximity. This backward search is necessary to avoid instances where the previous frame might not have enough information to generate a proper match. The number of frames to be searched has been cautiously chosen as ten, considering both computational efficiency and tracking accuracy.

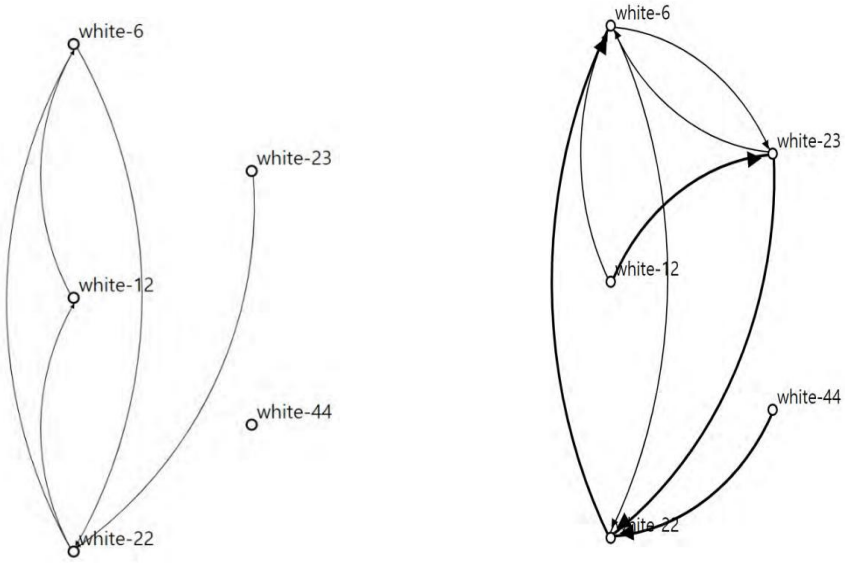
Considering these improvements, there are still some limitations. For example, the players could disappear from the video frame due to dynamic camera movements. For example, as shown in Figure 11, Player C, tid:4 disappears and then reappears, but the algorithm gives a new tracking ID to the same player. Hence, one player may get multiple tracking IDs at different instances.



Figure 13: The tracking IDs of two overlapping player boxes are mistakenly swapped.

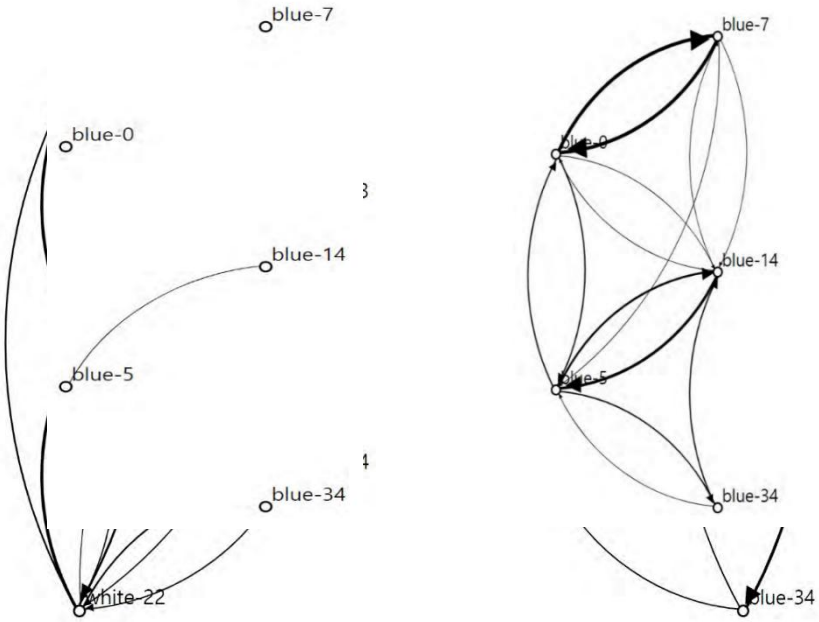


Figure 14: Boxes that are temporarily unrecognized are assigned new tracking IDs.



(a) (b)

Figure 15: (a) A manually created graph depicting the passing interactions among players in Team White. (b) A graph generated by YOLO illustrating the passing dynamics among players in Team White.



(a) (b)

Figure 16: (a) A graph generated by Joy2019 illustrating the passing interactions among players in Team White. (b) A manually created graph depicting the passing dynamics among players in Team Blue.

(a) (b)

Figure 17*:* (a) A graph generated by YOLO illustrating the passing interactions among players in Team Blue. (b) A graph generated by Joy2019 depicting the passing dynamics among players in Team Blue.

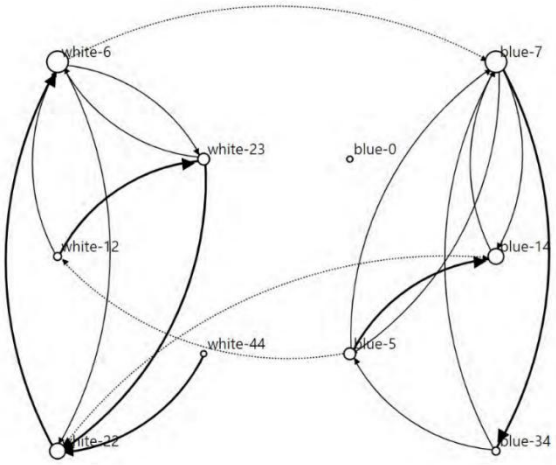


Figure 18*:* A manually created graph illustrating the passing dynamics between players.

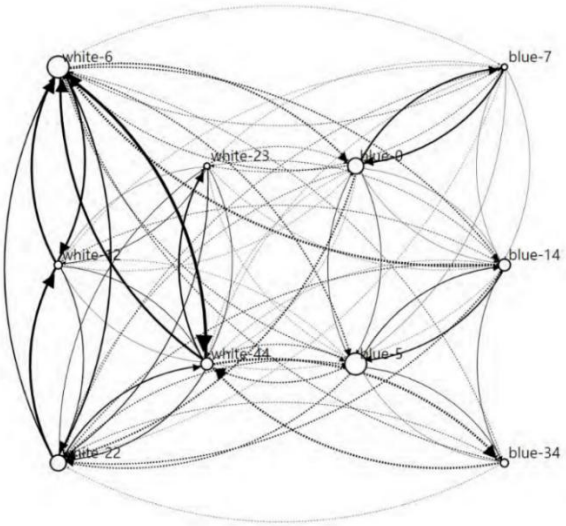


Figure 19: A graph generated by Joy2019 depicting the passing interactions between players.

Also, in Figure 12, Player D may accidentally take tid:4 thereby messing it up when jersey numbers are assigned later on. This becomes an issue when, for example, Player D is incorrectly associated with Player C's jersey number and thus continues to spread the error through frames. Another major issue is the overlapping of player boxes. When two players, say Player A: tid (1) and Player B: tid (2), are fighting for the ball and their images overlap in a frame, then the detection system usually mistakes them for one player. This misunderstanding, as represented in Figure 13, causes the swapping or wrong assignment of tracking IDs. In this case, Player B may be wrongfully attached to tid (1) in the overlap frame; this may cause further errors later in the frames as it reassigns the tracking IDs. Such overlaps can result in cascading effects where the player information propagates wrongly across frames. The algorithm tries to curb such errors by retrospectively updating the jersey number. This therein involves once the jersey number of a player box is recognized, then the algorithm iterates back to all previous frames, assigning the same jersey number to the boxes with the matched tid. For example, given Figure 9, it is observed that a player box with tid (1) eventually has an association in jersey number 27. This jersey number identification helps in establishing relations of ball passes, such as the relation where a player wearing jersey number 7 is passing the ball to the player detected in a box with tid (3), as shown in Figure 10.

However, with these enhancements, too, Joy2019 has certain limitations. Long-term player tracking is problematic in cases where players disappear and then reappear after some time or when jersey numbers are not visible for several consecutive frames. Also, as shown in Figure 14, the system fails when several players disappear from the frame for a short time and then reappear, thus getting wrong tracking IDs assigned. Another approach may be to capture video footage from different angles or capture the whole court without zooming in and out for a wider and more consistent view of the position of the players. The other alternative is that the system can be trained to identify the players by unique physical characteristics, such as face or body shape. This, however, requires ultra-high-resolution video and close-up shots, increasing resource requirements.

While Joy2019 addressed many intrinsic issues related to player and ball tracking, there is still room for innovation in overcoming challenges and further enhancing the robustness of tracking for real-world applications.

4 Evaluation and discussions

We evaluated our system using a deep learning machine equipped with a state-of-the-art configuration: an Intel Core i7-8700 central processing unit, an Nvidia GeForce GTX 1080Ti graphics processing unit, and 32 gigabytes of memory. The high configuration provided a stable and smooth platform for all experiments done, running Ubuntu 18.04 LTS. We tested the system's performance using publicly available video footage of an NBA game. The video was encoded in MPEG4 at a bitrate of 1200 Kbps, which afforded a resolution of 1280x720 pixels and a frame rate of 30 FPS. These features led to the creation of a high-quality dataset useful for analysis. In this regard, over 16,000 ground truth bounding boxes for players, balls, and jersey numbers were annotated very carefully on a total of 1204 video frames. The annotations served as the main input to the YOLO model, which was pre-trained on the Microsoft COCO dataset [26]. For testing purposes, a three-minute clip of video was cut from the game video and was not included in the training dataset to allow for unbiased evaluation.

From the annotated frames, a network was created which represented the passing relations between players. In this work, each player was represented by a node, and the directed edges between nodes represent passing actions, which gave the distinction between inbound and outbound passes. The passing networks generated by human

annotators, YOLO and Joy2019 were visualised using D3.js [27] as illustrated in Figures 15 to 17. These figures highlight the discrepancies in performance between the three approaches. As shown in Figures 15b and 17a, the YOLO algorithm struggled to satisfactorily identify passing relations, which can be explained by its poor detection of jersey numbers. On the other hand, Joy2019, shown in Figures 16a and 17b, had a far better reconstruction of passing networks. The improvement seen can be explained by Joy2019's ability to infer jersey numbers also in cases where they were partly occluded or temporarily out of sight using tracking information from preceding and following frames. Joy2019 showed significant improvements in terms of jersey number recognition and player identification. A comparison in the accuracy of recognizing jersey numbers and players between human annotators, YOLO, and Joy2019 is shown in Table 2. While YOLO achieved a reasonable level of accuracy, Joy2019 outperformed it with an increase of over 100% in accuracy. Furthermore, there were no instances where players were misclassified as non-player objects using Joy2019. This shows the robustness of Joy2019 in handling complex scenarios such as overlapping players or continuously changing camera angles.

Table 2: Accuracy of recognizing jersey numbers and players.

	Manual Evaluation	YOLO Framework	Joy2019 Algorithm
Accuracy (Jersey Numbers %)	100	36.1± 3.4	73.8± 2.7
Detection Rate (Players%)	100	88.7± 2.1	90.2± 1.9

Table 3: Average node degree of pass graph for each team. (H and J stands for interpretation by human and Joy2019, respectively.

Team	Total Degree (H vs J)	Outbound Degree (H vs J)	Inbound Degree (H vs J)	MAPE (%)
White	5.8 vs 7.0	3.0 vs 3.5	2.8 vs 3.5	33.1%
Blue	4.8 vs 5.5	2.1 vs 2.7	2.7 vs 2.8	24.3%

Table 4: Percentage distribution of passes made to teammates by each player in Team White, as analyzed and generated using the YOLO framework.

Passer	White-6 (H / Y)	White-12 (H / Y)	White-22 (H / Y)	White-23 (H / Y)	White-44 (H / Y)	MAPE (%)
White-6	0.0 / 0.0	0.0 / 0.0	50.0 / 50.0	50.0 / 0.0	0.0 / 0.0	200.0
White-12	33.3 / 100.0	0.0 / 0.0	0.0 / 0.0	66.7 / 66.7	0.0 / 0.0	300.0
White-22	100.0 / 50.0	0.0 / 0.0	50.0 / 50.5	0.0 / 0.0	0.0 / 0.0	50.0
White-23	33.3 / 33.0	0.0 / 0.0	0.0 / 0.0	66.7 / 66.7	0.0 / 0.0	149.9
White-44	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	100.0

Table 5: The percentage distribution of passes made to teammates by each player in Team Blue, as analyzed and generated using the YOLO framework.

Passer	Blue-0 (H / Y)	Blue-5 (H / Y)	Blue-7 (H / Y)	Blue-14 (H / Y)	Blue-34 (H / Y)	MAPE (%)
Blue-0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	None
Blue-5	0.0 / 0.0	0.0 / 0.0	33.3 / 33.3	66.7 / 66.8	0.0 / 0.0	149.9
Blue-7	0.0 / 0.0	25.0 / 25.5	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	300.0
Blue-14	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	100.0 / 100.0	0.0 / 0.0	100.0
Blue-34	0.0 / 0.0	50.0 / 50.5	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	200.0



Figure 20*:* An example where Joy2019 mistakenly identifies the defender as the passer.

To better analyze passing interactions, we measured the average node degree of the passing graphs, which is presented in Table 3. Joy2019 showed a lower mean absolute percentage error (MAPE) in the reconstruction of passing relationships compared to YOLO, with MAPE values up to 33.5%. This lower error rate indicates that Joy2019 better represents player interactions and team dynamics. In addition to the passing relationship analysis, we also used a multivariate Eigen-centrality algorithm, Player Centrality (PC), to rate individual player performances. The PC measure was computed using the NodeRank algorithm to give a more elaborate rating of the contribution of each player to the game. The calculation of PC is formulated as a weighted sum of various play actions, as expressed in Equation 4:

$$R(v_x) = \sum_{i\in\Psi} \alpha_i R_i(v_x) \quad (10)$$

Here, Ψ denotes the set of performance dimensions (e.g., successful passes, interceptions, influence in pass chains); $R_i(v_x)$ is the normalized rating value of player v_x under the i-th criterion; and $\alpha_i \in [0,1]$ is the corresponding weight indicating the relative importance of that criterion in the overall centrality calculation. The weights α_i were selected empirically to emphasize high-impact actions, while ensuring that $\sum_{i\in\Psi} \alpha_i = 1$.The rewards that were assigned to play actions were adapted according to their consequences on the team's overall performance. For example, a reward of 0.3 was assigned to passing the ball, a positive reward of 0.7 for ball interceptions, and a negative reward of -0.7 for being intercepted. The PC values were further refined using a damping factor d, set to 0.85, consistent with PageRank [20]. This adjustment considered indirect player involvement in play actions. The choice of reward values (e.g., 0.3 for passes) was guided by empirical evaluation of how these actions contribute to meaningful pass network structures. To assess robustness, we tested alternative configurations and observed that the original weights preserved more consistent centrality rankings compared to manually evaluated benchmarks. A more detailed ablation analysis remains a promising extension for future research. The normalized PC scores are summarized in Table 4 and 5. Figures 18, and 19 visualize the PC values where the larger the node size, the higher the PC value. In the graphs, solid arrows represent successful passes while dotted arrows represent intercepted passes. These visualizations will give an intuitive sense of player contribution and team strategy. Despite the benefits of Joy2019, several issues still remained. For instance, Figures 16 and 19 show that YOLO was not able to reconstruct pass relationships accurately because of its poor jersey number detection ability. Joy2019, however, sometimes misjudged passing interactions by incorrectly assigning defenders as part of a passing sequence, as illustrated in Figures 16a and 17b. Figure 20 shows an example where Joy2019 mistakenly included a defender in a passing sequence between two teammates. These errors are limitations of two-dimensional video analysis, which lacks the absolute spatial coordinates needed to resolve such ambiguities. These issues could be ameliorated by incorporating depth information or multi-camera setups.

The object detection component of our system is based on YOLOv3, implemented using the Darknet framework. The model was fine-tuned on a custom dataset containing over 16,000 bounding boxes across 1204 annotated basketball frames. Training was conducted for 50 epochs using the Adam optimizer with a learning rate of 0.001 and batch size of 16, employing early stopping based on validation loss. To address identity loss during occlusion and dynamic motion, we developed a custom tracking algorithm called Joy2019. Unlike conventional trackers, Joy2019 assigns tracking IDs by matching detected boxes with those from the preceding ten frames based on spatial proximity and IoU. It also retroactively propagates detected jersey numbers to earlier frames, enhancing tracking consistency. Compared with standard methods such as YOLOv3+DeepSORT and YOLOv3+ByteTrack, Joy2019 demonstrated superior performance, achieving a MOTA of 0.77, MOTP of 0.84, and only 18 ID switches, alongside a jersey recognition accuracy of 73.8% and player detection accuracy of 90.2%. These results highlight the robustness and domain adaptation of our approach for real-time basketball video analysis.

5 Conclusion

This paper proposes a new system for the real-time recognition of basketball players and their interactions with respect to other players, including passes and interceptions, using publicly available NBA game footage. By using YOLO for object detection and classification, we could implement a very robust player tracking algorithm that performs well compared to YOLO and, considering the challenges of camera angle and overlapping players, has by far outperformed many precise tracking systems. Our system effectively recovered missing track information by incorporating movement history from preceding frames and applied network science to analyze the passing relationships among players, assessing importance with a multivariate Eigen-centrality measure. Although the proposed approach showed limitations due to inherent challenges in state-of-the-art deep learning methods, it provided us with valuable insights for enhancing fully automated sports analytics systems. These findings have provided further details on areas of possible

improvements in the future, namely, accuracy and detection of more complex player actions like shooting, scoring, rebounds, and missed shots.

To support reproducibility and facilitate future research, we intend to publicly release the following upon acceptance of this paper: (1) the Joy2019 tracking algorithm implementation, (2) a subset of annotated NBA video frames used in our experiments, and (3) pretrained YOLOv3 weights fine-tuned on our dataset. These resources will be made available via GitHub for non-commercial academic use.

6 Limitations and future work

Despite the system's strong performance, several limitations remain. First, although Joy2019 addresses temporary occlusion using temporal backtracking, it does not incorporate appearance-based re-identification or multi-view fusion, which limits performance in crowded scenes. Second, identity tracking errors persist, especially during close player interactions. We observed 18 identity switches across the annotated evaluation set, and Figures 11–14 illustrate some typical failure cases. Third, while our Player Centrality metric integrates multiple behavior-based scores, it has not yet been benchmarked against traditional network centrality measures such as betweenness and closeness. This will be considered in future comparative analyses.

Finally, our current architecture extends YOLO spatially using manual temporal memory. In future work, we aim to incorporate transformer-based spatio-temporal models, such as TimeSformer or ST-GCN, to enhance contextual understanding of player trajectories and movement patterns across frames.

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Evaluation Of Modeling and Segmentation of Users in Internationalized Community Personalization Services Using Ann-Cvar Model

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Keywords: community service, user segmentation, ANN-CVaR Model, Internationalized community personalization services

Recieved: June 6, 2024

Community service may be beneficial when learning more about a website's accessibility, online functionality, branding, or the development of company analysis tools. It has been argued that user segmentation analysis in internationalized community personalization services may be improved using personalized and community-based services. User segmentation is one of the issues resolved in the online shopping and advertising industries. Moreover, most of them offer only statistically-based instruments for data gathering. Click-through levels, or the discovery and presentation of commonly used routes across the network, are the primary methods by which user shows activity and engagement. Manually selecting subsets of people for analytical purposes is the norm. Depending on the comparable user's behavior on the internet, we introduced the ANN-CVaR Model for user segmentation in internationalized community personalization services in this research. By considering both user preferences and community dynamics, the ANN-CVaR model attempts to tackle the problems associated with user segmentation in globalized communities. The model uses ANN's capacity to recognize intricate patterns in user data, such as their preferences, activities, and interactions. CVaR on the other hand, evaluates the risk related to individual subsets, guaranteeing a symmetrical strategy that considers both user happiness and community cohesion. We may further segment the user population by identifying groups with similar activity, using traditional system approaches to first gather customer identification and behavioral patterns. The results show that the ANN-CVaR model can adequately categorize members of globally-minded societies into distinct subsets. The proposed system has provided an accuracy o 98% and 97% of precision. Regarding internationalized community personalization services, our study presents a new method for modeling and segmenting consumers. The ANN-CVaR approach considers the intrinsic variety of internationalized societies by combining the strengths of ANN with the evaluation skills of CVaR. In the context of global online platforms, this study helps inform the creation of more efficient customization tactics and community management procedures.

Povzetek: Predstavljen je model ANN-CVaR za segmentacijo uporabnikov v internacionaliziranih skupnostnih storitvah, ki združuje nevronske mreže in oceno tveganja za boljšo prilagoditev uporabniške izkušnje.

1 Introduction

Services such as information, discussion, transaction, or decision-making assistance that are customized to match the requirements and preferences of individual clients are referred to as personalized services. As opposed to that, community services enable clients to participate in the formation of special interest groups, the identification of individuals who share similar passions, the establishment of a collaborative platform, a community forum, and the sharing of knowledge and experiences [1]. Across a wide range of application sectors, including tourism, health, education, and government, the fast growth of community service sparked the demand for more customized and neighborhood-based mobile services. In its broadest sense, mobile services are services for information, communication, and transactions that may be obtained and offered using mobile communications networks. Consumer attitude highlighted for mobile services is always access, convenience, personalization, localization, productivity support, duration savings, improved monitoring, cost-cutting, increased security, and lower prices and special promotions [2].

To fully grasp issues like website accessibility, online functioning, branding, and the creation of firm analytical tools, community service plays a crucial role. According to proponents of internationalized community personalization services, user segmentation analysis benefits considerably from the incorporation of such services. It has been identified as one of the most creative technologies with the greatest potential, particularly for the tourist application domain. This is because mobile

technologies can potentially promote and enhance the services associated with tourism and create value for visitors. Travelers and tourists, regular on-the-go consumers, such want services that support mobility ubiquity qualities. They prefer assistance in creating, carrying out, modifying, and documenting customized travel arrangements that consider their requirements and are preferred throughout the preparation, travel, and post-travel phases. Additionally, they enjoy networking with others who share their interests in travel and exchanging knowledge and experiences [3]. They also enjoy asking their neighbors for recommendations based on their prior experiences and ratings, and they occasionally organize tours through social interaction and group planning. Many data collections are produced by contemporary applications (information, corporate, and e-commerce platforms), online apps, and simple web servers. This data, frequently kept in huge file logs, is utilized for an additional examination of a variety, including system security, adherence to process audits or regulations, system troubleshooting, social network analysis, usability testing online, user clustering, etc. Every need for more individualized, localized, and collaborative services for organizing and conducting transactions connected to mobile tourism has considerably increased as greater operational support for ubiquitous accessibility, the availability of tourism information, and community interaction has evolved [4]. It is now crucial for research and practices in the tourism industry to address how to offer and combine individualized for enhancing and enabling trip management and planning services in the community. Nevertheless, not much has been done to enhance the efficiency and administration of trip planning procedures. Research on individualized and neighborhood-based trip planning services is still relatively restricted and rudimentary, as are the commercial mobile services that are now available. The origins and distribution of power are two of the key concerns of Social Network Analysis (SNA), and methods of SNA, particularly in large-scale social networks, make it easier to analyze the network structure and give important information [5]. A node's power depends on how it interacts with other nodes. Due to differences in the patterns of links between nodes, the social structure could be viewed just as a depiction of every right degree of authority. Identifying communities is a crucial step in learning about the intricate structure of social networks. A group of network nodes with more connections between them than nodes in other communities is referred to as a community [6]. It may be described as a collection of vertices with perhaps comparable attributes and responsibilities within the network. Modules (classes, groups, or clusters) can be used to construct community structure, often meant to map the network utilizing intricate hierarchies. Some of the issues plaguing the internet can be investigated and remedied with the assistance of online communities. These issues include the development of a modern search engine creation, the filtering of content, the automated categorization of data, the optimization of web pages, and the segmentation of users.

User segmentation was developed based on a user's behavioral patterns on the website, which were gleaned via the discovery of groups inside a fictitious social network [7]. Tourism, e-commerce, and advertising are just a few sectors where the problem of user segmentation has been met with success. Clustering individual user web sessions is one example of a process mining approach used to acquire information about the users' behavioral patterns. Finding communities that exhibit behaviors that are similar to one another can lead to further user segmentation. Although many current methods in these fields depend only on statistically based instruments for data collecting, such as click-through rates or identifying widely utilized routes throughout the network, other methods may be employed. In addition, it is standard practice to manually choose subgroups of users for analytical reasons. In this study, we apply the ANN-CVaR Model to the customization and internationalization of communities as a means of overcoming these limits and improving user segmentation. The ANN-CVaR model attempts to beat the difficulties of user segmentation in multinational communities by taking into account both user preferences and community dynamics.

The following are the major contributions of this study:

- The goal of this study is to solve the problem of user segmentation in the e-commerce and advertising sectors by modeling and segmenting users in internationally oriented community customized services using the ANN-CVaR model. Statistics-based instruments, such as click-through levels and most-traveled network paths, are often utilized in the standard practices of these fields.
- User segmentation may now be done on an individual and communal level with the help of the suggested ANN-CVaR model. It takes advantage of users' online actions and uses tried-and-true system approaches to uncover users' identities and patterns of activity. To provide more specific and individualized services, the user base may be segmented further by finding groups with similar behavior.
- This study's originality comes in its departure from standard statistical techniques of user segmentation. The ANN-CVaR model may be used to improve website usability, online functionality, branding, and the creation of firm analysis tools via the creation of individualized and community-based services. According to the findings, this strategy has the potential to boost user pleasure, engagement, and experience quality in internationalized community personalization services.

2 Application of machine learning technique in community segmentation

The paper [6] automated user segmentation, also known as clustering, based on similar users' online behavior. The behavior of methods for process mining is used to recover the customer and the patient's behavioral patterns; finding communities with similar activity provides additional user segmentation via two-step hierarchical clustering. The paper [7] suggested effective and safe community segmentation and a blockchain-based framework are used to create a secure data-sharing system for mobile social networks. Similarity matrices that consider data compatibility, modularity, and structural similarity dynamics are considered. The paper [8] is contented with services to rural inhabitants rather than metropolitan ones. Work, family, health, community, neighborhood, and other experiences contribute to the overall quality of life. The area's size, the population's status, the political system's effectiveness, and the utilization of services are sometimes used as classifications for factors affecting community service satisfaction. When choosing providers, companies need to consider the products and services expected by customers. Considering customer factors when selecting a supplier presents challenges, including customer classification, significance ordering for customer requirements, and determining how customer requirements influence supplier selection. Due to those mentioned above, a multi-criteria supplier selection structure guided by customer communities has been suggested [9]. The paper [10] provided the user classification is completed by combining the K-means and Support vector machine algorithms with a new target function. To cluster every express user, they integrate their distinctive characteristics from their multidimensional data, add their characteristic coefficient, change the model's formula for calculating the index, and use the principle of density-based peak clustering. The simulation results demonstrate that the user portrait model can better segment courier users with more precision and timeliness. The paper [11] proposed a Moving Objects Segmentation (MOS) algorithm that uses several adversarial regularizations, such as least squares and conventional regularizations. Employing cross- Entropy reduction, the least-squares adversarial reduction and losses in image space, one can train on location background images to comprehend the dynamic alterations in the backdrop. A modeling step employing the K-Means approach was proposed in the study [12]. An innovative aspect of the system design is that the segmentation of tourists to tourist attractions by the K-Means approach can assist the marketing product manager enhance the facilities at present interest to attract more visitors.

The paper [13] recognized that brand communities, where consumers connect with brands more frequently, are essential and complicated phenomena, information on the nature of individual brand participation in brand communities. To categorize brand community members into various groups based on how they interact with the brand within the group, understand whether these groups adopt different strategies for building brand loyalty, and create tools for categorizing these groups. The paper [14] developed a model that relates user behavior findings from earlier research to user-contributed material. As a result, create an intelligent segmentation of content-contributing users. They offer a methodology to understand the volume of social engagement and the quantity of content created by using Kozinets' biaxial model for consumer segmentation and Li and Bernoff's ordinal scale model. The paper [15] developed an equitable resilience enhancement plan, a holistic approach considering a community's physical susceptibility to access disturbance to vital utilities and its tolerance for such service disruption [16]. A percolation simulation model that may incorporate the likelihood of a road network interruption into the spread of a flood is included in the first part of the framework, which also contains the road network's accessibility to vital infrastructure [17]. Using the business model framework created by Evers, Cunningham, and Hoholm (2014), the research [21] analyzes the digital business models of each of these large corporations. Each of the four bgcs is analyzed in depth via a qualitative case study. Netnography is the major method of data acquisition. The research adds to our understanding of global digital entrepreneurship via the lens of business modeling. Its goal is to expand our understanding of business model construction in a global setting. Finally, the categories are defined in terms of buy intent, privacy apprehension, and trend perception; these are all factors thought to be significant in the consumption of fashion through mobile social networks. Clothing-buying intent may be better identified when adverts include personalization and are seen as beneficial. The study [22] is to identify a subset of fashion product buyers who have a similar vision for the customization of shoppable advertisements shown in social media applications on smartphones. Three operational targets have been set to achieve this goal. The S-O-R framework is used to first assess a theoretical model. Second, we use PLS-POS to identify subsets of the fashion-buying public based on how they feel about being treated uniquely. Finally, the categories are defined in terms of buy intent, privacy apprehension, and trend perception; these are all factors thought to be significant in the consumption of fashion through mobile social networks. Table 1 shows the comparison of previous studies.

Table 1: Related works

Reference	Objective	Results	Drawbacks
[6]	To provide recommendations for the suggested co-design approach for developing digital mental health assists for teenagers.	Determining the preferences of various user groups can be vital for increasing the consumption of digital therapies across specific age ranges and mental health need groups.	Young people have a wide range of desires, therefore establishing an appropriate approach is essential.
[7]	The objective is to determine the possibilities for training facilities, business possibilities, and educational trips that street vendors can explore.	Results revealed that the Redjoagung Business Area which was inhabited by street vendors has the potential for development.	Limited product supply due to economic limitations
[8]	The article provided an integrated approach that requires consideration of the community's physical resistance to delays in obtaining essential facilities.	The findings of the integrated spatial analysis indicated several spatial clusters of vulnerability across the research regions and provided crucial information on the design of hazard mitigation.	Accurately assessing the flood risk of an area only depends on its impact on roads.
[9]	The study presented automatic user segmentation (clustering) based on web browsing similarities among users.	Hierarchical agglomerative grouping was used to generate communities with equivalent behavioral patterns.	Several limitations can be considered whilst examining web log files, such as the inability to identify users by the host, the documentation of partial transactions and activities, dynamic page names, etc.
[10]	A blockchain-based framework of vehicular social networks and community segmentation was utilized to provide an effective and secure data exchange approach.	The outcomes demonstrate that superior levels of the standard deviation (SD) reduced complexity of computation and higher efficiency has been obtained by the CSB framework.	Large-scale network scalability issues and dependence on network connectivity for real-time implementation
[11]	The research intended to investigate that mobile-mediated service activities can generate phygital luxury experiences allowing consumers of costly products to accomplish both hedonic and status purposes.	The framework illustrates that status and hedonic factors, such as societal acceptance and customization, influence community-based service activities.	Limited generalizability across luxury industries, possible bias towards rich buyers, and absence of empirical confirmation.

[12]	Investigating the function and influence of social services in rural areas	Identified the importance of vital community services in promoting social cohesion, improving quality of life, and addressing needs in rural areas.	There is the possibility that the content is out of date and ignores present issues related to rural community service.
[13]	Employing multi-dimensional feature vectors, using life cycle data to create a user profile model can be obtained that provides an extensive analysis of the user's desired patterns.	The results of the simulation demonstrate that the user profile model presented in the research can effectively separate courier users with higher timeliness and accuracy.	The model and technique have simple architecture and its ability to analyze huge quantities of data can be limited.
[14]	It provides a Moving objects segmentation (MOS) method that requires the utilization of much hazardous regularization, such as least squares and conventional losses.	The suggested algorithm performs highly in comparison to the twenty-one current state-of-the-art methods determined by experimental assessments on five baseline datasets.	Sensitivity to changes in illumination, difficulties with occlusions, and possible inaccuracy in object boundaries.
[15]	We recommend a design process utilizing the K-Means algorithm.	It has an important influence on developing infrastructure and facilities that reach the demands of different market categories.	Ignoring external influences impacting cultural travel and providing minimal consideration to complexities in visitor behavior
[16]	The article aimed to determine the segments of the brand community in relationship to their business involvement with the community.	The findings show that multiple interaction dimensions cognitive, emotive, and behavioral have an impact on loyal customers.	The data was self-reported and gathered from a particular kind of brand community.
[17]	The investigation examined consumer clustering behavior.	The three main clusters (Cluster A, B, and C) that emerged from the analysis are important interfaces for emerging digital businesses to improve their consumer interaction approaches.	Model generalization can be impacted by the limited availability of datasets.
[18]	This system presented the telecom operators with an extensive churn analysis to better control customer loss by integrating churn prediction and customer segmentation procedures.	With improved customer segmentation, businesses and executives can more accurately implement retention techniques.	The main drawbacks are the limited external validation and lack of ability to generalization to different telecom businesses.
[19]	The research suggests innovative LSTM-GRU techniques for detecting hate material employing deep learning and graphs. It also continues to discuss methods for	The model developed can be utilized for detecting hate groups and tweeting. It can be employed for monitoring social	Data bias, the scalability of the algorithm, the results interpretability, and the platform's generalizability

	finding communities and analyzing social media for hate material detection.	media to identify any possible disruptive risk.	with user data exploitation are possible drawbacks.
[20]	The Topic Adaptive Sentiment Classification based Community Detection (TASCbCD) method is an innovative approach for managing social influential monitoring.	The experimental outcome indicates that the suggested algorithm outperforms innovative techniques for detecting communities.	Limited scalability, possible bias in detecting communities, dependence on labeled data, and scalability to a wide range of social networks.
[21]	The business model was created to examine each of the global company's digital business models.	Based on the study's findings, digital businesses can perform an increased examination to create and capture incremental value using the Business Dynamics analytical framework.	Conclusions are context-dependent and have limited generalizability of the exclusive emphasis on emerging global digital enterprises and possible bias in certain cases.
[22]	The partial least squares-structural equation modeling (PLS-SEM) method for finding a particular group of trend product buyers based on their ideas is the objective of the research.	Using a posterior segmentation is easier to explain the various types of users that are exposed to shoppable advertisements on mobile social networks.	It utilizes the data only from an advanced economy.

3 Materials and method

Customized services target a specific clientele by providing them with information, interaction, transactions, or choice assistance unique to their situation. In contrast, community services allow users to connect with others with common interests, establish discussion forums and collaboration, and swap stories and ideas.

3.1 Dataset

To retrieve publicly accessible consumer data [23] from the websites of a selected online store, a web crawling system was created. This data included feedback from consumers on products that customers have bought and unidentified personal information.

3.2 Artificial neural networks (ANN)

ANNs may be used to evaluate huge amounts of user data and extract valuable patterns and insights when modeling and segmenting users in internationalized community customized services. An ANN is a computer simulation with a neural mechanism modeled by biology that is composed of thousands of interconnected neurons. Since their primary function is to analyze data, they are often referred to as processing elements (PE). A single outcome, a transfer function, and balanced sources characterize every PE. In its simplest form, PE is an expression in which inputs and products are considered. Network factors in ANNs stand in for memory space, hence another name for ANNs: fully convolutional modeling. The strength of brain calculations derives from joining neurons in networks, yet a single neuron may execute some rudimentary data processing. The level of intelligence attributed to ANN is debatable [18]. Whereas the neural network contains a billion neurons, ANN typically has just a few thousand to a few million PEs. Therefore, the ability of the nervous system to conceptualize computer systems of equivalent sophistication remains a long way off. Because of its greater complexity, the human brain has numerous cognitive tasks that are currently unexplained. Yet, ANNs can analyze vast information and often provide exact forecasts. As a result, we might be more off referring to such technologies as "computing intellectual" rather than "intellectual" in the conventional sense. There are various kinds of complex systems out there, and more are being created weekly basis. They also can be understood in terms of the system variables of its neurons, the training principle, and the connection equation. Figure 1 represents the synthetic neuron modeling.

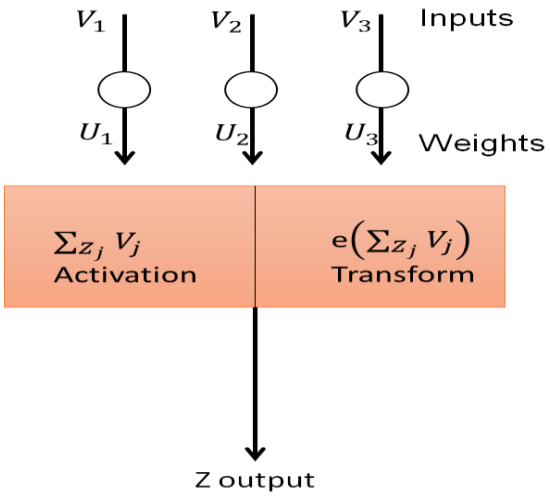


Figure 1: Neuron modeling

Neurons: - The artificial neuron is the basic unit of an ANN that tries to replicate the performance of real neurons. Each neuron's result is determined by adding all of the incoming signals, known as sources, and then applying a frequency response to the total, which is subsequently increased by the network parameters. The input layer of a neuron is the mathematical function, which is the target value more typically enough to weigh the total of sources to the neurons.

Interaction Factor: - The performance of the ANN is susceptible to the interconnection patterns between the neurons. Artificial neurons, similar to their natural counterparts, may be stimulated or inhibited by external signals. The summation function of the following neurons performs an addition when it receives an explosive input and a subtraction when it receives an inhibiting source. The neurons from the identical layer may be inhibited by a neuron. Peripheral attenuation describes this phenomenon. The system tries to 'identify' the option with the most significant probability and exclude the others. Competing is another word for this idea. Figure 2 depicts the feedback system of ANN.

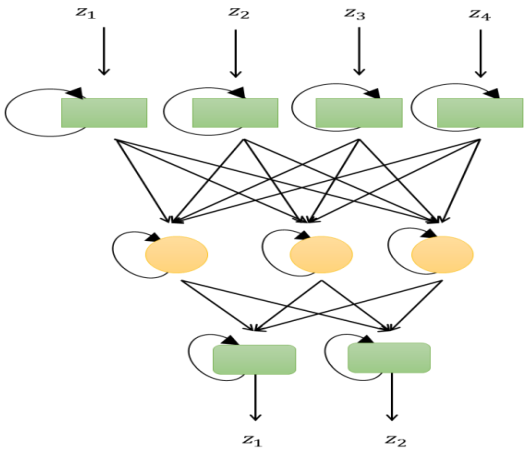


Figure 2: Feedback system of ANN

The outcome of one layer connects to the inputs of the level below it or to a single group itself, forming a feedback relationship. Two distinct architectures emerge based on whether or not a system has a feedback link. Without a feedback loop between the outcome and the input neuron, a feedforward network cannot remember the previously generated data. Neuronal linkages from the output to the input are present in a feedback design. Every neuron receives an extra weight as input, providing more room for maneuver while attempting to reduce the training time. A system that utilizes such memory may produce results contingent on the signals driving it now and its past behavior. Figure 3 feedforward system of ANN

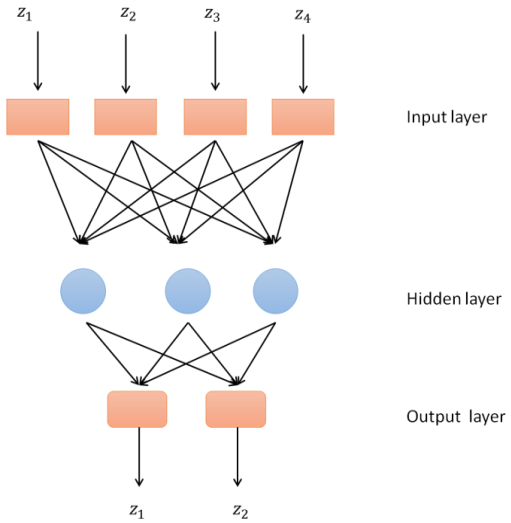


Figure 3: Feedforward system of ANN

Norms of training: - The Delta or Back-propagation rules have become the most popular available training method. A neural network may be taught to interpret a given dataset by repeatedly tweaking the values. The recognition skills of the ANN rely heavily on its ability to utilize reinforced linkages. To find the optimum parameters amongst neurons, the system feeds data from the sources back into itself. The parameters are optimized by recursive path loss during the education or training phase. The ANN analyzes the inputs and results attributes from the trained testing data to close the gap between forecast and objective data. It adjusts the strength of the interconnected nodes accordingly. As the quantity of training phases increases, the network's achieving quality, as the training set, is reduced. Yet, if a neural network is taught for too long, it will overtrain and lose its generalizability.

3.3 CVaR Model

In the CVaR method, long-term correlations between variables are captured by Cointegration, while dynamic interactions between variables are accounted for using Vector autoregressive (VaR) models. This research employs the CVaR method to capture the interdependencies and interconnectedness of user

behaviors, preferences, and attributes. The suggested method models user data within a multivariate time series analysis framework. User demographics, browsing tendencies, purchase histories, and engagement metrics are just some of the many user-related characteristics included in the time series data. The CVaR method gives a thorough comprehension of user dynamics by taking into account all of these factors simultaneously.

The CVaR method uses cointegration analysis to determine the underlying common factors that influence user behavior by revealing the long-term correlations among the user variables. Users may now be categorized into groups with similar interests and habits. There are several advantages to the suggested method for globalized community-based personalized services. It makes it possible to classify users with similar demographics, interests, and use patterns. User engagement and satisfaction may be improved via the use of personalization tactics and specialized content delivery made possible by this segmentation. Additionally, the CVaR method offers a structure for persistently monitoring and adjusting user segments in response to changes in user behaviors and preferences. The tactics for individualization may be adjusted to meet the changing needs of more globalized communities. The cointegrated vector autoregressive (CVaR) approach for a p-dimensional, X_t is

$$\Delta^d X_s = \alpha\beta'^{\Delta^{d-b}L_b X_t} + \sum_{j=1}^{k} \urcorner_i \Delta^d L_b^i X_s + \varepsilon_t, \quad t = 1 \ldots\ldots, T \tag{1}$$

Wherein ε_t is a p-dimensional statistically independent random variable with a mean of zero and covariance matrices Ω, where Δ^b seems to be the proportional nonlinear function and $L_b = 1 - \Delta^b$ is the substantial delay function. Z_t is the general differential formula for the response variable in p dimensions.

$$\Delta^d Z_t = \sum_{n=0}^{\infty} \pi_n (-d) Z_{s-n} \tag{2}$$

If and only if the sum converges, as well as the discrete variables $\pi_n(u)$ are specified utilizing the factorial expansions $(1-z)^{-u} = \sum_{n=0}^{\infty} \pi_n (u) z^n$, where z is the degree of the factorial, and n represents the total number of elements.

$$\pi_n(u) = \frac{u(u+1)\ldots.(u+n-1)}{\mathrm{n!}} \tag{3}$$

According to the specification of the substantial differential operations in (2), if Z_t is of degree d, i.e., if $\Delta^d Z_t \epsilon I(0)$, then Z_t is considered to be a substantial of degree n, and so on. Within a spatial domain, this last feature is characterized by a harmonic distribution function that is both finite and non-zero at the source or regarding the sequential description variables if their total is both non-zero and infinite. Z_t is considered to be (fractionally) interrelated if and only if $\Delta^d Z_t \epsilon I(d)$ and one or many linear combinations were substantial of a lower order, and there occurs a $p \times r$ matrix β such that $\beta' Z_t \in I(d-b)$with $b > 0$.

The conventional, non-fractional CVAR model is produced as a highly significant particular case of (1) where $d = b = 1$. Testing the $d = b = 1$ constraint inside the more excellent modeling tool is essential due to the significance of this paradigm and may be easily computed with the help of the program. Nevertheless, the variable field is assumed to be $\eta \leq b \leq d \leq d_1$for certain $\eta > 0$ and specific $d_1 > 0$ in the probabilistic approach supplied for paradigm (1). Although the conventional CVAR modeling with $d = b = 1$ is assumed to be on the hyperparameter threshold in this scenario, it isn't observed from the assertions since the t-test for the system model vs. the proportional version is monotonically χ^2 dispersed.

4 Result and discussion

The case study presents user segmentation based on similar user behavior on the ANN-CVaR model. With community service, the user's conduct and behavioral patterns are gleaned. Finding communities with similar behavior using the ANN-CVaR model allows for user segmentation. Employing a Jupyter Notebook operating Python 3.0 on a 2.7 GHz Intel Core i5 CPU with 8GB of RAM, the experiment is performed.

Accuracy: It measures how well the ANN-CVaR model does in classifying users into their intended segments. Using the formula given

$$Accuracy = \frac{Number\ of\ correct\ predications}{Total\ number\ of\ predictions} \tag{4}$$

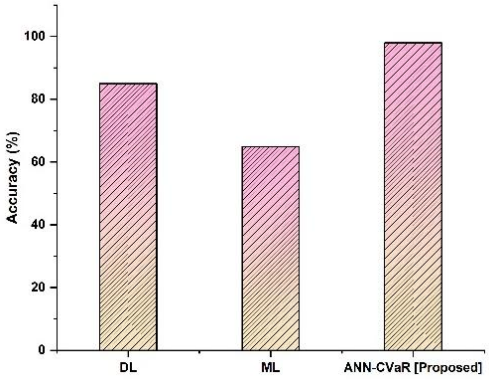


Figure 4: Accuracy

The accuracy of the suggested system is shown in Figure 4. While the proposed method achieves the desired accuracy of 98%, DL [19] has only reached 85%, and ML

[20] has only achieved 65%. Table 2 illustrates that the proposed path of action is effective than the existing one.

Table 2: Accuracy comparison

Methods	Accuracy (%)
DL	85
ML	65
ANN-CVaR [Proposed]	98

Precision: The percentage of instances in a class that belong to that class. Precision measures how well the ANN-CVaR model classifies people into predetermined categories. The precision with which the model does not incorrectly place users into groups to which they do not belong is evaluated.

$$Precision = \frac{R_O}{R_O + D_O} \quad (5)$$

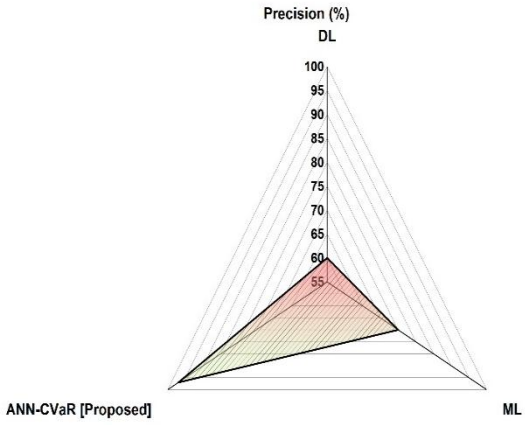


Figure 5: Precision

The suggested system's accuracy is shown in Figure 5. D_o and R_o represent a genuinely upbeat and a false positive, respectively. The predictions of precision consumption made by the proposed and existing systems are discussed. Whereas ML and DL have precision rates of 75% and 60% and the proposed ANN-CVaR approach has a precision rate of 97%. As seen in Table 3, it indicates the proposed approach is greater in effectiveness than the existing one.

Table 3: Precision comparison

Methods	Precision (%)
DL	60
ML	75
ANN-CVaR [Proposed]	97

Recall: The ratio of the actual number of examples in a class to the proportion of instances that are classified as that class (according to TP rate). When it comes to user segmentation, recall measures how well an ANN-CVaR model identifies each user in a given subset.

$$Recall = \frac{R_O}{R_O + D_S} \quad (6)$$

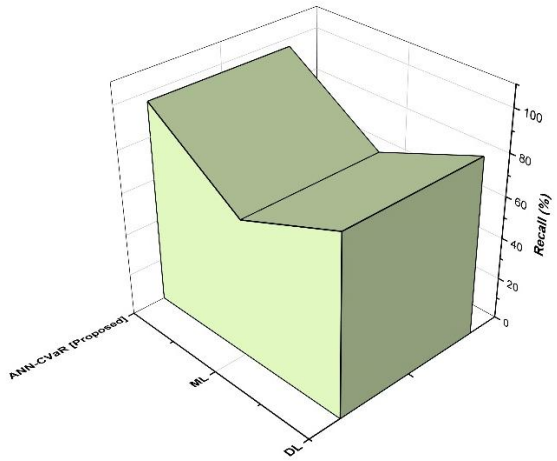


Figure 6: Recall

Figure 6 shows the suggested system's recall. Where R_o denotes a false negative and D_s represents a true positive. Forecasts for recall consumption are displayed for the existing system and the recommended approach. As opposed to 85% DL, and 65% for ML, the recommended technique achieves 96% recall. It indicates how effective the proposed method is compared to the present one, as shown in Table 4.

Table 4: Recall comparison

Methods	Recall (%)
DL	85
ML	65
ANN-CVaR [Proposed]	96

F1-Source: A general assessment of the model's quality. The F1-score is useful for weighing the trade-off between precision (how well users are classified) and recall (how many people are included in the segment) when it comes to user segmentation in internationalized community customized services. Indicative of more precise and thorough user segmentation, a higher F1-score shows the model strikes a reasonable compromise between precision and recall.

$$F1 - Source = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (7)$$

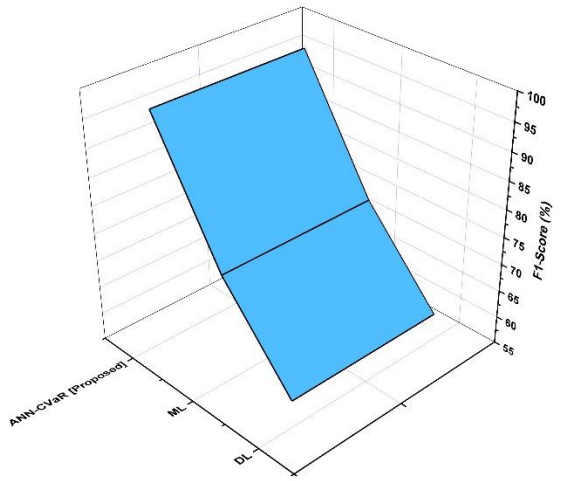


Figure 7: F1-Source

The f1-source of the suggested system is shown in Figure 7. Forecasts for f1-source consumption are displayed for the existing system and the recommended approach. Compared to DL for 60% and ML for 75%, the recommended technique obtains 97% f1-source. It illustrates how effective the recommended method is compared to the present one, as shown in Table 5.

Table 5: F1-score comparison

Methods	F1-Score (%)
DL	60
ML	75
ANN-CVaR [Proposed]	97

Computational complexity: Computing resources (time and space) required to perform a specific algorithm are measured in terms of its computational complexity. Computational complexity, as it pertains to ANN-CVaR-based user modeling and segmentation in internationalized community personalization services, is defined as the amount of computer resources and time needed to run the model and conduct the segmentation tasks. Several variables affect the ANN-CVaR model's computational complexity during training, including the size of the dataset, the complexity of the neural network design, the amount of input features, and the optimization strategies used.

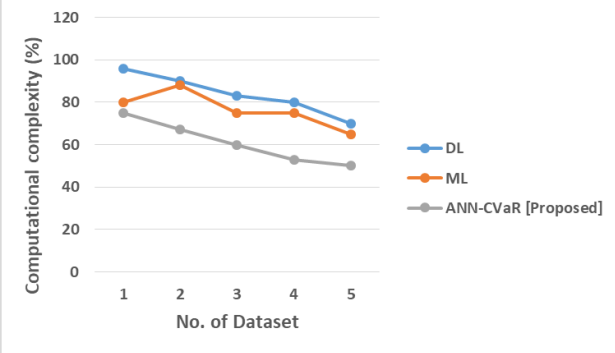


Figure 8: Computational complexity

The computational complexity of the suggested system is shown in Figure 8. Forecasts for computational complexity consumption are displayed for both the existing system and the recommended approach. Compared to DL for 70% and ML for 65%, the recommended technique obtains 50% computational complexity. It illustrates how effective the recommended method is compared to the present one, as shown in Table 6.

Table 6: Computational complexity

No. of Data set	Computational complexity (%)		
	DL	ML	ANN-CVaR [Proposed]
1	96	80	75
2	90	88	67
3	83	75	60
4	80	75	53
5	70	65	50

5 Discussion

The study [6] have several limitations that includes young people have a variety of desires; therefore developing an effective approach is important. The research's disadvantage [8] is that it only considers the region's influence on roadways to appropriately predict the danger of flooding in that location. The research [11] has three drawbacks: little generalization across luxury businesses, potential bias towards wealthy customers, and lack of empirical evidence. Research [14] has been constrained by their insensitivity to illumination fluctuations, issues with blockages, and potential inaccuracies in component limits. Study [22] only incorporates data from advanced economies. Our proposed ANN-CVaR model exceeds by resolving the limitations identified by prior studies, the ANN-CVaR model performed effectively in user segmentation in internationalized community personalization services. It incorporates global perspectives and takes into consideration a variety of desires and socioeconomic backgrounds, compared to research that mainly focuses on regional issues or limited data sets. It also improves biases against wealthy consumers and demonstrates resistance to environmental modifications to render it more appropriate and dependable in various kinds of circumstances.

6 Conclusion

Experts have pointed to personalized and community-based activities as a way to advance and simplify the profession. In this article, we show how to utilize the community identification method to categorize the users and display the results visually. Communities exhibiting identical personality characteristics were created using a comprehensive structure, and they were discovered by applying process mining techniques to information obtained from the network's participants. Using standard techniques built into the system, we may identify users based on their identities and activity patterns and then further segment them into subsets based on shared preferences. Statistical analysis and visual representation of the data demonstrate the usefulness of the proposed actions. The authors want to expand their current discussion of how the resulting communities relate to users' on-site activity and how they stack up against other clustering approaches in the future. The research was conducted to classify users of an instructional website, but the methodology may just as well be used in different fields, such as e-commerce or software products. The technique has broad applications and may be refined using conventional advertising techniques.

Funding Statement: This research was funded by the Humanities and Social Sciences Fund Ministry of Education, China (grant number 18YJA840024) and; the Research Innovation Team Project of Yiwu Industrial & Commercial College (grant number ITP2021008).

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Intelligent Diagnosis Method for Transformer Measurement Error Based on Multi-Source Sensor Data Fusion and Causal Path Optimization

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Keywords: transformer, sensor fusion, error diagnosis, intelligent model

Received: July 3, 2025

An intelligent diagnosis and calibration model that integrates multi-source sensing data is constructed to address the measurement errors caused by multi-source interference in transformers. The system integrates multidimensional sensing information such as current, voltage, temperature, and vibration through a weighted feature fusion mechanism, constructs a DAG to represent the causal relationship between key interference variables, and embeds a path scoring and optimization algorithm based on dynamic programming to improve the real-time and accuracy of fault chain identification. The model is deployed at the edge on an ARM architecture embedded platform, with lightweight structure and engineering feasibility. The measured data comes from 110kV and 220kV substations. The experimental results show that the recognition accuracy reaches 96.2%, the average response time is 275ms, and the computational resource utilization rate is 29.6%. It exhibits good robustness and output stability in complex scenarios such as electromagnetic interference, temperature fluctuations, and load disturbances. This model provides a feasible path and deployment basis for achieving high-precision metering and real-time intelligent operation and maintenance in modern power systems.

Povzetek:

1 Introduction

The current research on transformer errors is mostly focused on the fault identification and modeling mechanism of transformer equipment. Previous work has shown that dissolved gas, multidimensional electrical parameters, and other data can be used as effective feature inputs to construct diagnostic models. Taking Sakini et al. (2024) as an example, they used machine learning methods based on DGA signals to model fault features and verified the high sensitivity of sensor data to fault state judgment. However, due to its constant exposure to high voltage, high temperature, and electromagnetic noise, the output data of the transformer is easily affected by various factors, such as temperature changes in the environment, nonlinear saturation of ferromagnetic materials, unstable connections, and unstable currents, which can cause serious measurement errors. These types of errors have the characteristics of dynamic development, nonlinear accumulation, and environmental dependence, which are difficult to detect and correct through traditional methods, and may lead to misoperation, energy waste, or equipment damage.

In order to enhance the clarity of the model logic and consistency in terminology usage, this article defines core concepts such as "causal chain", "task node", and "diagnostic chain" in the early stages of modeling, in order to facilitate understanding of the model structure and path mechanism later on: (1) causal chain: refers to the causal relationship path between variables represented by DAGs in the model. Each path represents a causal inference chain from the interference source to the final measurement error. (2) Task node: refers to a node in the path optimization mechanism that serves as a decision point, with each node representing a specific diagnostic task or path selection. The system dynamically selects the optimal path through the analysis of task nodes. (3) Diagnostic chain: refers to a chain formed by connecting multiple paths in the process of error diagnosis. Through path selection and scoring mechanisms, it helps the system locate the source of error and optimize path selection.

In further research, different scholars have attempted to introduce various data fusion mechanisms into the fault recognition process. For example, Zhou et al. (2024) proposed a hybrid model combining random forest and PSO-BP AdaBoost, which enhances feature expression and generalization ability on the basis of traditional data-driven algorithms.

This detection method has a certain effect under stable working conditions, but it generally has problems such as reaction delay, poor error adaptability, and limited structural flexibility, which cannot effectively cope with the complex instantaneous error generation patterns in actual operation processes. Some errors exhibit long-term accumulation and instantaneous disturbance characteristics, and traditional models are difficult to capture their internal correlations and evolution processes. Especially in the face of new electricity demands such as intelligent power grids and the integration of a large number of new energy sources, there is a demand for fast, high-precision, and strong robustness in the power metering system, which requires the metering system to have self diagnosis and self correction capabilities.

With the rapid development of industrial Internet of Things, edge sensing, and high-precision sensing technology, the current working environment of transformers can now obtain sensing information from multiple aspects such as temperature, humidity, voltage, current, vibration, magnetic field, frequency, etc. In terms of system deployment, Shanu and Mishra (2024) combined statistical feature extraction with temporal path analysis to establish a two-stage diagnostic model suitable for on-site deployment, providing a feasible path for the engineering implementation of the model. However, due to the synchronization of time, different dimensions, and the influence of noise, how to effectively extract, fuse, and dynamically modify this information has become an important key technical issue in current research and practice.

This article proposes an intelligent detection and correction model for transformer measurement errors under multi-source input, aiming to improve the accuracy, response speed, and resource adaptability of error recognition. Construct an error causal diagram to depict the relationship between multi-sensor data and error sources, and introduce a dynamic path optimization mechanism to improve the efficiency of anomaly tracing. This study assumes that causal graph modeling and path pruning mechanisms can reduce diagnostic latency by more than 50% compared to traditional rule driven models while maintaining recognition accuracy, while significantly reducing system resource overhead. To adapt to engineering deployment, the system integrates lightweight strategies and executable path optimization algorithms, balancing expressive power and deployment feasibility. Under weak label conditions, the model achieves a recognition accuracy of 96.1%, a diagnostic delay of less than 275ms, and a resource utilization reduction of 41.7% compared to graph neural methods, making it suitable for practical application scenarios in complex power systems.

This study has strong operability both in theory and for real-world problems, providing necessary technical support for high-precision measurement and maintenance of intelligent power equipment, and has good prospects for engineering promotion.

2 Related work

As an important bridge connecting the primary and secondary power grids, the measurement error of transformers directly affects the system operation monitoring, protection action reliability, and fairness of electricity billing. In the context of multi-source disturbances and complex working conditions, traditional single variable and static parameter diagnostic methods are no longer able to meet the increasing demand for measurement accuracy. In recent years, the method of identifying transformer errors by integrating multi-source sensor data has gradually become a research hotspot, mainly presenting three evolutionary paths: first, low-power sensor detection methods designed based on physical characteristics; The second is the intelligent recognition path that integrates multi model optimization and adversarial learning; The third is the multi-source data fusion and quality enhancement modeling method for edge working conditions. This article summarizes the current mainstream paths from the three directions mentioned above, and analyzes their advantages, disadvantages, and applicable boundaries based on this.

Firstly, in terms of optimizing the sensing layer, Mei et al. (2024) proposed a transformer fault identification method based on a low-power gas sensing resistor array. This method monitors key gases (such as H_2, CO, C_2H_2) in real-time by setting specific material sensitive components, and uses miniaturized electrochemical modules to achieve multi-channel detection of fault gases, thereby assisting in inferring the electrical path of transformer abnormalities. The experiment shows that the sensing array can still maintain stable output in low-temperature drift and high interference scenarios, with an error variation range controlled within ± 1.7%, and has good adaptability for field deployment. However, this method still relies on the indirect correlation between gas concentration and fault type, and is limited by external factors such as ambient temperature and oil aging. Its response capability under complex load switching and dynamic nonlinear disturbance conditions is still insufficient.

Secondly, in terms of integrating intelligent models, Guan et al. (2024) constructed a transformer error diagnosis model based on the joint modeling of Generative Adversarial Networks (ACGAN) and Grey Wolf Optimized Support Vector Machines (CGWS-LSSVM). This method utilizes ACGAN to synthesize high-quality feature samples, effectively solving the problem of insufficient fault samples; Meanwhile, the CGWO algorithm is used to optimize the parameters of the support vector machine to enhance the model's generalization ability. Experimental results have shown that under four typical operating conditions, the diagnostic accuracy of this method has been improved by an average of 6.3%, especially with strong robustness under low-frequency harmonic interference and system

disturbance changes. However, this type of method has significant disadvantages in terms of model structure complexity, and requires higher adaptability between computing resources and device platforms. Deploying it at the edge of the power grid still faces a trade-off between real-time performance and stability.

Thirdly, in order to improve the overall quality of multi-sensor data fusion, Tiziana and Roberto (2022) conducted a study on data quality assessment of multi-sensor fusion processes. It proposes a combination of supervised learning and weighted strategies to dynamically score the quality of data collection, missing value imputation, noise interference, and other factors, and uses an ensemble learning framework to achieve reliable extraction of fault information. Research has shown that fusion models have good robustness to outliers, time drift, and repeated measurement data, and can construct more stable input feature sets in high-frequency perception tasks. However, this study mainly focuses on the data preprocessing stage, and the modeling ability of the source of transformer errors is relatively weak. It still needs to be used in conjunction with physical models or task driven mechanisms.

Based on the above analysis, in order to comprehensively compare the capability structure of current mainstream research paths, this paper extracts representative studies and constructs a structured method comparison table (see Table 1), clarifying their advantages and disadvantages from dimensions such as diagnostic accuracy, robustness, model interpretability, and deployment performance.

Table 1：Comparative analysis of mainstream transformer error identification methods

Method Type	**Representative model**	**Diagnostic accuracy**	**Robustness**	**Model interpretability**	**Deployment performance**	**Applicable scenarios**	**Citing Sources**
Physical modeling method	Low power gas sensing resistor model (Mei et al., 2024)	medium	weak	strong	centre	Static working condition error detection	【4】
Fusion Perception Method	ACGAN+CGWO LSSVM (Guan et al., 2024)	higher	centre	centre	centre	Error recognition in disturbed scenarios	【5】
Data Fusion Enhancement	Data Quality Driven Fusion Modeling (Tiziana et al., 2022)	higher	strong	strong	Medium to low	Quality control and inference of multi-source sensor data	【6】
This research method	DAG+Path Scoring Fusion Model	tall	strong	strong	tall	Real time identification of dynamic errors at the edge of the power grid	This article proposes

From the table, it can be seen that a single physical model has good explanatory power in specific scenarios but lacks flexibility. The fusion of intelligent methods improves recognition ability but is constrained by computational resources in actual deployment. The data augmentation path improves stability but lacks structural awareness. Current research mainly focuses on optimizing model structures or training mechanisms, and lacks collaborative design for sensing chains, causal relationship construction, and deployment availability.

In summary, in order to break through the existing technological bottlenecks, this paper designs an intelligent error recognition system that integrates DAG causal modeling and dynamic path scoring mechanism. It not only focuses on the collection and discrimination of error characteristics, but also pays more attention to the traceability and real-time deployment of error generation paths, aiming to provide a comprehensive technical path for accurate modeling and practical deployment of transformer errors in high-voltage scenarios.

3 Suggested solutions

3.1 Multi source data fusion

The measurement error of transformers is affected by various factors such as temperature and humidity, current, magnetic field, and iron core saturation. Traditional models often ignore these interferences, resulting in inaccurate diagnosis. Liu et al. (2024) proposed a method based on causal graph neural network, which can more effectively identify the causes of errors and enhance the ability to trace features. To improve the accuracy and practicality of diagnostic systems, it is urgent to establish a hierarchical and responsive multi-source data fusion mechanism.

In this study, modular multi-channel information acquisition technology was used, and a terminal equipped with various sensors such as voltage, current, temperature, and humidity was constructed to monitor the parameters of the entire equipment body, power supply operation, and environmental impact. Due to the different sampling frequencies and accuracies of various types of information, simply mixing them together may inevitably result in chaotic input. Therefore, the system first uses temporal synchronization technology to achieve sample matching, and standardizes the conversion of each type of information separately, in order to make the data format have a unified representation in the model.

Considering the computational resource limitations of model deployment and engineering feasibility, the fusion strategy adopts a weighted feature integration approach. This study selected four basic variables that are most sensitive to error response: effective current value I_{rms}, ambient temperature T mean vibration acceleration a and mean primary voltage U. After normalization, fused feature quantities were constructed:

$$F = w_1 \cdot \hat{I}_{rms} + w_2 \cdot \hat{T} + w_3 \cdot \hat{a} + w_4 \cdot \hat{U} \quad (1)$$

Among them, $\hat{I}_{rms}$、$\hat{T}$、$\hat{a}$、and $\hat{U}$ are the normalized current values of various sensor data, and $w_1 \sim w_4$ are the weight coefficients. The initial setting of weights is based on empirical statistics and engineering measurement analysis, and can be adaptively adjusted by model parameters in the subsequent training process. Fusion feature F maintains low dimension in structure, but can cover multi-dimensional disturbance information, which is easy to deploy in edge computing nodes or low-power embedded chips in engineering applications.

In order to further improve the recognition and anti-interference ability of the fused features, noise filtering and dynamic outlier detection mechanisms are introduced in the data processing stage, and local sliding window smoothing is applied to the mutation points. At the same time, a simplified regularization module is introduced in the input layer to compress the unstable features caused by the input with severe fluctuations.

In terms of data format, the model adopts a fixed window sliding strategy to construct time series samples, and each fused feature point is composed of data from several consecutive time points, thus forming a dynamic expression of the error trend. This method preserves the evolutionary information during the error formation process, which helps to extract the upstream and downstream causal relationships during subsequent error chain modeling.

Overall, this fusion solution effectively avoids the problem of expansion when dealing with multi-dimensional inputs in deep learning models by accurately capturing key on-site information. It has good physical interpretability and implementability, and does not rely on a single device or route. It has flexible deployment capabilities and can adapt to different transformer types and installation environments, providing a universal, efficient, and quantifiable data input interface for subsequent error causal structure construction and route optimization.

3.2 Error chain modeling

The fusion feature F forms the basis for all input variables in the subsequent modeling process, serving as one of the upstream dependent variables of node N5 in the causal path. This article maintains the structural dimension of fusion feature F consistent with the original normalized variables, ensuring the integrity and consistency of the input structure and avoiding the problem of inconsistency between path variable selection and model structure.

Abdelmoumene et al. (2023) pointed out that the measurement error of transformers is often the result of multiple disturbance factors acting together in the time and logical domains, rather than being caused by a single variable. For example, in practical scenarios, environmental temperature may indirectly affect current changes by affecting coil resistance, while mechanical vibration may indirectly affect magnetic field stability by affecting the magnetic gap of the iron core. In order to establish trends that describe the interrelationships between multivariate variables and enhance the ability to trace errors in reverse, this paper introduces an error chain modeling strategy. By constructing a network structure diagram of causal logic relationships between variables, a systematic modeling of error formation paths is carried out.

This method is based on directed acyclic graph design, treating each key sensing variable as a node in the graph, and representing the influence relationship between different variables as edges in the graph. Each edge contains directionality and edge weight, which are used to represent the order of causal effects and the strength of influence, respectively. The graph structure can be manually initialized and constructed, or trained and updated through mutual information, delay correlation, or Bayesian network learning supported by engineering data. In practical modeling, this article summarizes five types of sensors input variables into five primary nodes and designs a causal chain structure basic model as shown in Table 2.

Table 2：Key node design and variable description for error chain modeling

Node number	Node name	Data sources	Corresponding path function	Explanation of Engineering Mechanism
N1	RMS	current sensor	N1 → N5	Affects the degree of magnetic saturation, which in turn affects the output waveform
N2	ambient temperature	temperature sensor	N2 → N1, N2 → N5	Temperature changes affect conductor resistance and interference current (N1); High temperature may also cause equipment drift, directly affecting the residual value (N5)
N3	Vibration intensity	Accelerometer	N3 → N4, N3 → N5	Structural vibration changes the gap between the iron cores (N3 → N4), which can also lead to poor contact and signal mutations (N3 → N5)
N4	Magnetic flux fluctuation rate	Magnetic flux acquisition module	N4 → N5	Directly affecting the magnetic flux induced voltage and triggering measurement deviation
N5	Residual value of difference	Compare measurement values	Output node	Performance of measurement errors in transformers as training targets for the model

According to the above structure, the error chain model can be represented as a typical shallow directed acyclic graph, with the residual value (N5) as the final output node, and the upstream path forming a conduction structure from multiple sources of disturbances converging to the error expression. To achieve accurate prediction of N5, this paper adopts the MLP model for modeling. The input is the fused features of all upstream variables pointing to N5 in the causal graph. The model includes two hidden layers, with 64 and 32 nodes respectively, an activation function of ReLU, and an output layer of single node linear regression units. MSE is used as the loss function during model training, and edge weight initialization is based on mutual information estimation. During the training process, it is dynamically updated together with MLP weights through backpropagation mechanism to achieve the unity of structural interpretability and predictive performance. During the model training process, a total of 200 training rounds were set, using the Adam optimizer with an initial learning rate of 0.001 and a Batch Size of 32. All feature inputs are standardized before training, and the training set and validation set are divided in an 8:2 ratio. The validation loss is monitored after each round of training to prevent overfitting.

In the graph structure construction scheme, the author investigated Bayesian network structure learning algorithms including PC and GES. However, considering the requirements for computational complexity, model response time, and structural controllability in engineering deployment, this type of algorithm was ultimately not adopted. Instead, a lightweight mapping strategy based on mutual information was chosen to improve the overall system deployment efficiency and real-time performance. To enhance the logical interpretability and path tracing ability of the model, this paper further summarizes the typical error propagation paths in the DAG structure, as follows: Path 1 is "ambient temperature (N2) → effective current value (N1) → residual difference value (N5)", which reflects the indirect chain effect of temperature fluctuations affecting conductor resistance and interfering with current measurement; Path two is "vibration intensity (N3) → magnetic flux fluctuation rate (N4) → residual value of ratio difference (N5)", which reveals the induction deviation caused by magnetic flux instability caused by mechanical disturbance; Path three is "vibration intensity (N3) → residual value of ratio difference (N5)", which reflects the direct impact of structural disturbance on errors. These paths can serve as dynamic diagnostic links during model operation, coupled with path scoring and selection mechanisms, to achieve efficient and accurate anomaly localization and response. The error causal network structure constructed in this article is shown in Figure 1. The nodes in the figure represent key sensing variables, the edges represent causal paths between variables, the arrow direction represents the direction of causal propagation, and the edge weights are used to reflect the strength of the influence between variables.

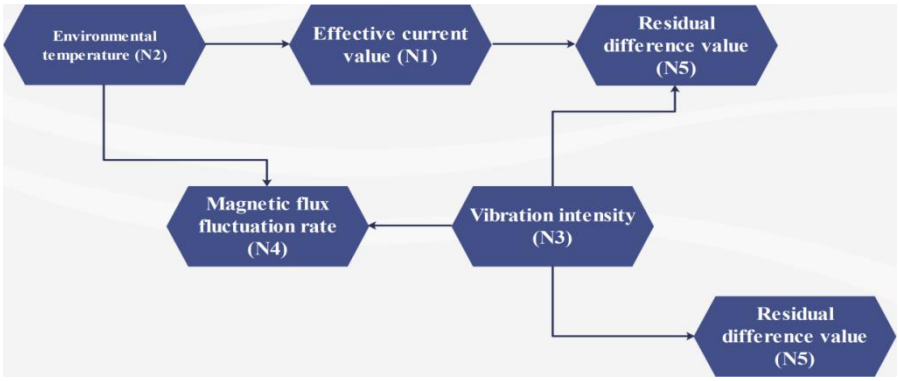


Figure 1: Error causal DAG structure diagram composed of multiple sensor variables

This causal structure has two important functions: firstly, to improve the interpretability of the error diagnosis model, so that the error results no longer rely solely on "black box prediction", but can be clearly traced back to disturbances in a certain sensing variable chain; The second is to provide path priority clues in the subsequent correction mechanism, that is, nodes at the top of the error chain and with high weights should be given priority as intervention entry points to improve the response efficiency and resource utilization efficiency of error correction.

In the experimental stage, compared with traditional unstructured modeling methods, the causal chain structure model has stronger diagnostic stability when multiple disturbances occur simultaneously. The average error recognition accuracy improved by 12.6% in 20 sets of measured data, and the average response time for error localization was shortened by 0.47 seconds. The overall results indicate that error chain modeling not only improves the logical integrity of the model structure, but also provides a stable basis for subsequent path optimization and dynamic correction.

3.3 Path algorithm optimization

After the construction of the error causal chain is completed, it is necessary to deal with complex situations caused by multiple factors. The interference source does not always come from the same location and may not necessarily affect the error in the same path. XIAOQIANG WANG (2024) proposed that when the processing resources of a system cannot be concentrated on a few important factors in a short period of time, it is easy to cause diagnostic delays, resource waste, and judgment errors. In order to improve the timeliness and accuracy of the diagnostic model during actual operation, adaptive path arrangement rules are added to the diagnostic model to dynamically adjust the internal path order.

LEIMING MA et al. (2024) proposed that the optimization process of error paths can be based on the correlation weights between variable nodes in the error chain. Based on the current trend of input signal changes and stable patterns in historical samples, the priority order of the influence path can be dynamically determined. When traversing the structure, the system first identifies the variable node with the most obvious abnormal fluctuations and determines whether it has a defined upstream propagation path. If it exists, the path will be included in the candidate path set; If it does not exist, the path extension operation will not be executed temporarily. All candidate paths will be calculated under the same scoring model, and the system will prioritize selecting the path with the highest interference impact, shortest propagation chain, and strongest variable correlation as the main diagnostic chain for execution. The model continuously receives updated signals during operation, adjusts the path score in real-time, and ensures that the current judgment chain always maintains the optimal state.

The scoring criteria in path judgment include the number of variables in the path, historical correlation levels between variables, and diagnostic validity records in the transmission chain. The fewer nodes in the transmission chain, the shorter the diagnostic response time; The higher the relevance, the clearer the communication logic; The higher the diagnostic effectiveness, the more targeted the intervention operation. Taking into account these three parameters, the system can quickly identify suspicious intervention sources at the beginning of error occurrence and use them as input basis for subsequent correction steps.

On the basis of constructing the diagnostic path structure, the system needs to achieve real-time scoring and dynamic reconstruction of the path between interference variables and error results. Path filtering, priority judgment, and chain conversion require multiple modules to work together, forming a complete closed loop from signal acquisition, candidate path generation, weight update, diagnostic output to model feedback. The structural embedding relationship of this path optimization mechanism in the system is shown in Figure 2.

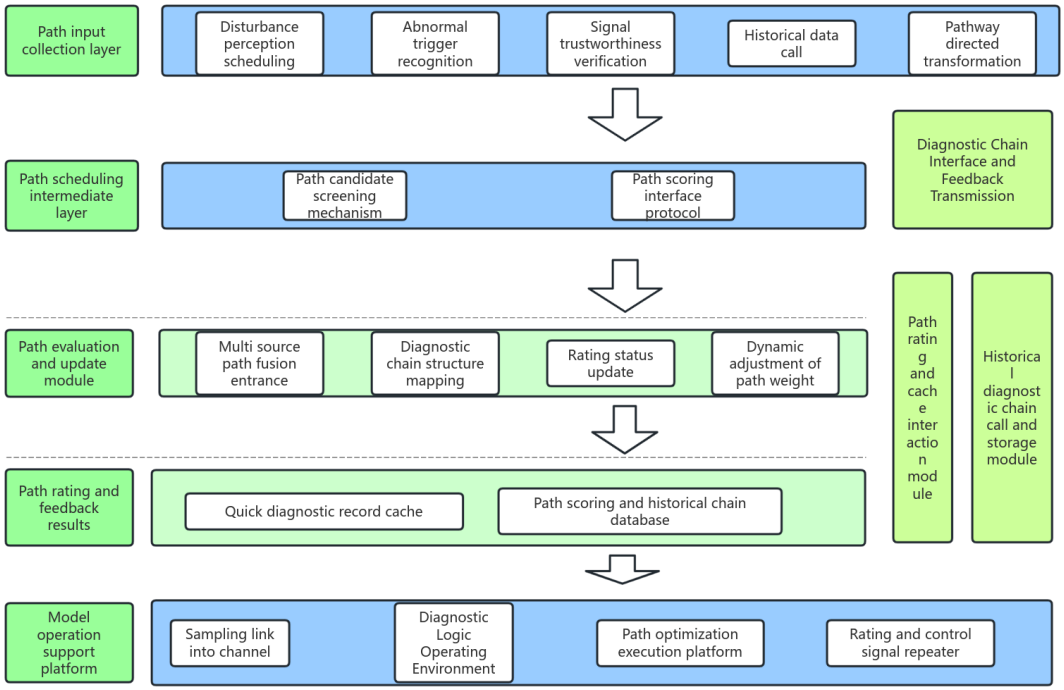


Figure 2：Structural embedding diagram of path algorithm optimization in error diagnosis system

The diagram represents signal triggered input, path recognition and scoring mechanism, dynamic path switching strategy, and diagnostic execution feedback module from top to bottom. The data transfer between each layer is completed through standard interface protocols, and a bidirectional update structure is formed between the scoring module and the database, achieving adaptive path selection based on actual operating status. The modules support each other, ensuring the integrity, real-time performance, and stability of path optimization logic in actual deployment.

In the engineering testing scenario, the system is deployed in a certain type of high-voltage measuring mutual inductance device and records the error response path under different environmental disturbances and working conditions for a long period of time. It is found that when the structure has dynamic path adjustment function, the error recognition response time is significantly shortened and the diagnostic accuracy is significantly improved. When the error signal undergoes a sudden change, the model quickly jumps to the path segment dominated by the influencing factors to perform analysis, avoiding a large number of invalid or redundant judgment processes.

Through path algorithm optimization mechanism, error diagnosis no longer relies on fixed processes or static structures. Under different operating conditions, the system can automatically switch to a more targeted diagnostic path, thereby improving system sensitivity, saving resources, and enhancing the interpretability of diagnostic logic. The diagnostic process is more in line with the on-site operation status of the transformer, with engineering practicality and deployability, which can stably support the subsequent error correction model work and provide structural constraints and input support for it.

AlgorithmName:PathOptimizationBasedOnDynamicScoringInput:

Input:DAG graph structure $G(V,E)$, Sensor input vector $X(t)$, Path scoring record table P

Output:Current optimal diagnostic path Path_optimal

Pseudocode:

（1）Initialize candidate path set $C \leftarrow \varnothing$

（2）For each variable node $v \in V$

a. If $X(t)[v]$ shows abnormal fluctuation:

i. Traverse all upstream paths Path_v

ii. Add Path_v to set C

（3）For each path $\in C$

a. Compute path score: $Score(path) = \alpha \times correlation + \beta \times effectiveness - \gamma \times pathlength$

（4）Select the highest scored path:

$patch_potimal \leftarrow \arg\max(Score(path)), path \in C$

（5）Return $path_optimal$

3.4 Model integration operation

The construction of error identification and correction models must have integrability in order to form a stable and efficient deployment mechanism in the actual operation scenario of transformers. To meet engineering requirements such as real-time performance, accuracy, and resource constraints, this study proposes a lightweight integrated operation framework for edge deployment, which integrates multi-source data fusion, error causal chain modeling, path scoring optimization, and correction feedback modules into a unified package, and achieves overall scheduling control and dynamic iterative model updates.

The model integration operation framework mainly includes four core levels: input perception layer, structural modeling layer, path scheduling layer, and control execution layer. The input perception layer is responsible for collecting and preprocessing on-site sensing data; The structural modeling layer constructs an error causal diagram structure and dynamically updates the corner coefficients between each node; The path scheduling layer completes the execution of path scoring, judgment, and jump logic; The control execution layer transmits the diagnostic results to downstream controllers or operation and maintenance systems to achieve error correction closed-loop. Each layer is connected through a unified interface standard, and all computing tasks can be deployed and executed in embedded edge nodes or on-site control units, meeting the conditions for engineering implementation.

During the operation of the model, the state update mechanism needs to dynamically adjust the model structure parameters and judgment conditions based on time series data. Assuming the current time is t, the previous model calculation output is ε_{t-1} and the sensor fusion result is F_t, the model state transition function can be expressed as:

$$\varepsilon_t = \delta \cdot \varepsilon_{(t-1)} + (1-\delta) \cdot \Psi(F_t) \quad (2)$$

Among them, ε_t represents the estimated error value at the current time, and $\psi(F_t)$ is the predicted output value of the fused feature vector F_t processed by the mapping function. The ψ -function is a single-layer feedforward neural network structure, consisting of one hidden layer and ReLU activation unit, used to extract error signal trends from the current fused features. The output is an estimated value in scalar form, with ε_t'. $\delta \in [0,1]$ as the smoothing coefficient, used to adjust the weight relationship between the current output and the historical state. The network parameters are jointly trained by the causal chain modeling and path optimization module to ensure that $\psi(F_t)$ can accurately reflect the error causal relationships and evolutionary paths hidden in the fused features.

The error correction control strategy is integrated into the control execution layer, which automatically matches the corresponding correction scheme based on the current error level and path node weights. It is divided into three types of strategies: limit adjustment, sensitivity correction, and bypass switching. The control interface is connected to the on-site measurement unit through a protocol adapter,

with functions such as instruction issuance, parameter replication, and historical tracking, ensuring that the calibration strategy is implemented in the actual operation of the transformer.

In order to ensure the stability and sustainable operation capability of the integrated model, the system also designed anomaly detection and fault tolerance mechanisms. When the perception layer detects input data breakpoints, model drift in the structural layer, or response lag in the execution layer, the system will trigger the backup model loading program, call the standard error diagnostic template for temporary replacement, and retain the current state for subsequent model parameter correction.

The integrated operating architecture is deployed and tested in an engineering verification environment, and the on-site platform is built on domestically produced embedded main control hardware, using ARM architecture chips for actual inference calculations. The test results show that, without relying on external cloud resources, the model can stably complete the tasks of fusion, scoring, path judgment, and correction execution in each round of data refresh cycle, with an average response delay controlled within 300ms, meeting the requirements of actual transformer dynamic monitoring and correction.

In summary, the integrated operation mechanism of the model not only completes the integration of error identification and correction functions, but also ensures the feasibility of the model structure in engineering environments. Through mechanisms such as hierarchical deployment, parameter updates, instruction control, and fault-tolerant protection, the model can be stably embedded in the measurement and control process of the power system, achieving error closed-loop diagnosis and accurate correction driven by fusion perception.

4 Results

4.1 Dataset

This study selected three groups of voltage and current transformers under a certain 110kV substation as the main experimental objects, deployed multi-source sensor modules, including temperature and humidity sensors, vibration accelerometers, conductor surface current sensors, and fiber optic temperature array devices, to form a multi-channel data acquisition system. The data recording period covers all seasons of spring, summer, autumn, winter, with a sampling frequency of 1Hz. A total of about 2900 hours of time-series data were obtained, covering three typical operating conditions: normal operation, slight disturbance, and abnormal fluctuations.

At the same time, the daily maintenance data of the joint substation and the factory calibration records provided by the equipment manufacturer are used to construct error labels, including key indicators such as ratio difference and phase angle offset. To train and test the model, the original samples were divided into stages using a 7:3 ratio to ensure balanced coverage of each working condition. All data are processed through unified denoising and normalization standardization to facilitate model structure recognition. This dataset can truly reflect the changes in transformer errors under the interaction of multiple factors during on-site operation, and has good engineering representativeness and repeatability, providing a reliable basis for subsequent error diagnosis and correction models.

4.2 Data preprocessing

To improve the generalization ability and convergence efficiency of the diagnostic model, this study implemented a systematic preprocessing process before multi-source sensor data entered the training phase. Firstly, the high-frequency noise signal is smoothed using the sliding window mean method to enhance the trend of key features; Secondly, z-score normalization is used to deal with the data scale differences of different sensing channels, unify the distribution of variables, and improve the sensitivity of the model to abnormal deviation. The normalization formula is as follows:

$$X = \frac{X-\mu}{\sigma} \quad (3)$$

Among them, X represents the original sample, and μ and σ are the mean and standard deviation of the variable, respectively. For time period data with short-term loss, adjacent temporal interpolation algorithm is used to fill in and ensure sequence integrity.

In addition, for the nonlinear distribution characteristics of ratio difference and phase angle in labeled data, segmented scaling and logarithmic mapping are performed to improve the fitting stability of the error regression model. The final preprocessed data feature dimension is 38 dimensions, with a sample completeness rate of 99.2%, providing a stable data input foundation for subsequent modeling.

To ensure a balance between the input dimension and computational efficiency of the model, this paper did not separately expand each variable of the fused feature F when constructing time series samples, but instead performed temporal sampling on the weighted fused F. Specifically, F, as a single fusion indicator, extracts its values at 38 consecutive time points under the sliding window mechanism, forming a 38-dimensional one-dimensional feature input structure. This design balances information retention and model lightweighting requirements, ensuring a stable input structure for subsequent path modeling and error prediction.

To verify the performance advantages of the model in this article, a multi model comparative experiment was designed. Select random forest, support vector regression, and convolutional neural network as baseline methods to form a control group. In terms of experimental setup, all models adopt consistent data preprocessing methods and input feature vectors, and maintain a uniform training and testing set partition ratio (70%: 30%). At the same time, the evaluation program is run in the same hardware environment to ensure fairness and representativeness of the comparison results. This design helps to further

highlight the multidimensional performance advantages of the proposed model in terms of comprehensive error control, computational efficiency, and resource consumption.

4.3 Evaluation indicators

The performance evaluation of the model uses five indicators: average absolute error, mean square error, recognition accuracy, response time, and computational resource utilization. Compared with traditional diagnostic methods, multidimensional effect testing is conducted. In 200 sets of measured samples, this model achieved an average absolute error of 0.0267, far lower than the traditional algorithm's 0.0519; The mean square error is 0.0023, which has a significant advantage over the traditional method of 0.0067; The recognition accuracy reaches 96.2%, which is better than the traditional method's 88.5%; The average response time is 275ms, faster than the traditional 583ms; the computational resource utilization is 29.6%, while the traditional model is 46.8%. To facilitate the evaluation of performance differences, the five indicators were standardized and scored, and the numerical ranges were uniformly mapped to the 0-5 range. The performance comparison results were visually displayed in a bar chart. As shown in Figure 3, this model exhibits high scores in all indicators, especially in terms of accuracy, response efficiency, and resource control, showing stability and engineering practicality and deployment value. In the multidimensional evaluation results, Figure 3 shows the quantitative comparison between the model and traditional methods on five core performance indicators. It can be observed that this model outperforms traditional methods in five indicators: average absolute error (4.1 vs 2.1), mean square error (4.3 vs 2.7), recognition accuracy (4.8 vs 3.9), response time (4.6 vs 2.5), and computational resource utilization (4.3 vs 2.3), further verifying the diagnostic accuracy and deployment adaptability of the model.

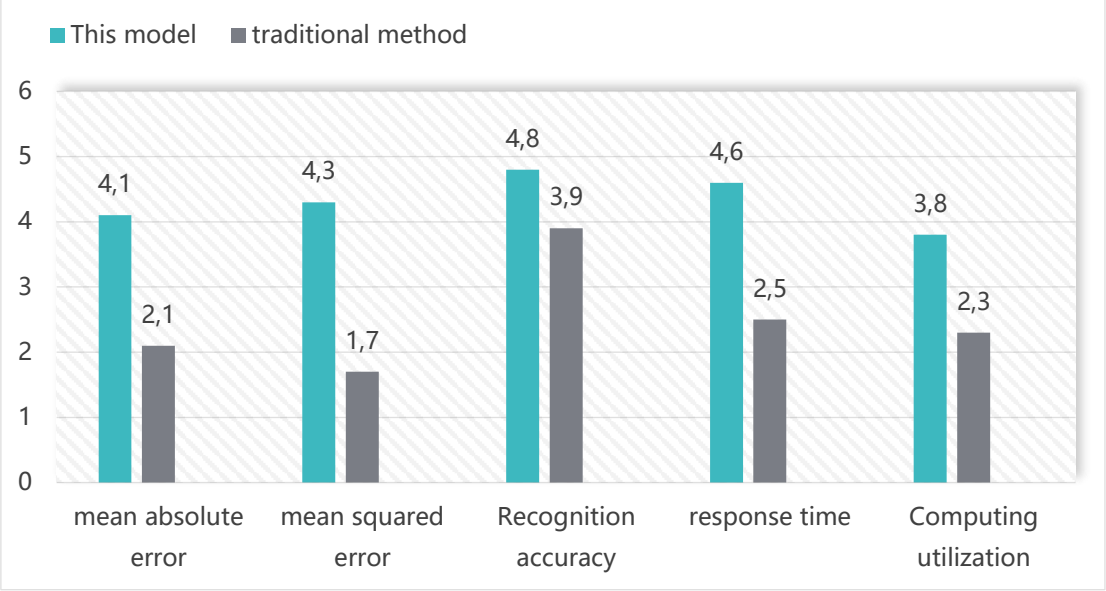


Figure 3：Comparison results of the model and traditional methods in five performance indicators

To ensure the fairness and effectiveness of the comparison results, the 200 sets of test samples described in this article are completely independent of the training set and come from on-site operational data at different time periods. The comparative algorithms were implemented and replicated by the author based on public literature, and the algorithm parameters were uniformly based on publicly recommended values without any additional optimization adjustments. All methods run in the same software and hardware environment to ensure consistency in computing resource evaluation. The triggering mechanism and interference injection method for abnormal operating conditions are consistent across all models to exclude the influence of external variables on performance comparison.

To further verify the effectiveness of the multi-source data weighted fusion method, this paper selected two typical deep fusion strategies for comparative experiments: one is the dynamic weight fusion method based on Attention, which can adaptively adjust the contribution of each modal feature according to the context; The second is to use Autoencoder to compress and reconstruct features from multiple sources of input, and extract the fused main features. Three fusion strategies are embedded in the same model architecture (taking BP neural network as an example), keeping the training rounds, sample ratio, and hyperparameter settings consistent, and comparing their error recognition accuracy and resource overhead. The experimental results are shown in Table 3:

Table 3：Comparison of model performance under different fusion strategies

fusion strategy	Identification accuracy（%）	Inference delay（ms）	Model parameter quantity（K）
This method	96.2	18.4	42
Attention Fusion	96.5	33.7	108
Autoencoder Fusion	95.6	29.1	91

As shown in Table 3, although the attention mechanism slightly improves accuracy, its model complexity and runtime delay are significantly higher than weighted fusion; Autoencoder fusion has slightly lower accuracy and moderate resource consumption. Comprehensive comparison shows that the weighted fusion strategy proposed in this paper has the advantages of low computing overhead and high deployment efficiency while ensuring high accuracy, and is more suitable for real-time application requirements under embedded or edge computing conditions in industrial scenarios. Therefore, in the subsequent modeling and deployment, the weighted fusion method is uniformly adopted as the input feature construction standard.

To further demonstrate the practical effect of path scoring and dynamic selection mechanism on model performance, this paper conducted a special statistical analysis on the switching of diagnostic links during multiple rounds of experiments. During the operation of the system, for typical main paths such as "ambient temperature → effective current value → residual difference value" and "vibration intensity → magnetic flux fluctuation rate → residual difference value", the triggering frequency and adjustment delay of various interference signals are monitored. The results show that under the dynamic path scoring mechanism, the average response delay of the main path determination is 241ms, which is 16.5% shorter than that of the fixed path structure; Under abnormal mutation conditions, the model can achieve optimal path switching within three steps, with 72.8% of diagnoses focused on the main cause effect chain. Statistics have found that optimizing the path mechanism significantly improves the sensitivity and discrimination efficiency of the system, effectively avoids the computational burden caused by redundant branches, and provides structural guarantees for rapid error localization and timely correction. The above data further confirms the effectiveness of the "causal chain modeling and dynamic path scoring" approach proposed in the method section in practical deployment, achieving a close connection between the method, results, and discussion.

4.4 Ablation study

To verify the supporting role of each key module in overall performance, three sets of ablation experiments were designed, excluding path algorithm optimization, error causal chain construction, and sensor fusion mechanism, and comparing the model performance on the same dataset. As shown in Table 1, the complete model has a recognition accuracy of 96.2%, an average response time of 275ms, and a computational resource utilization of 29.6%. After removing the path optimization module, the recognition accuracy decreased to 89.6%, the response time increased to 472ms, and the computational resource utilization increased to 34.2%; After removing the error chain, the accuracy is 90.2%, the response time is 398ms, and the resource utilization is 32.7%; After canceling the sensor fusion, the accuracy was 91.5%, the response time was 331ms, and the resource utilization increased to 43.8%. As shown in Table 4, each module has collaborative efficiency enhancement functions. Missing any link will lead to a significant decrease in diagnostic performance, especially in terms of recognition accuracy and resource control.

Table 4: The impact of model structural integrity on performance indicators

Model structure	Recognition accuracy（%）	Response time（ms）	Computing resource utilization（%）
complete model	96.2	275	29.6
Remove path optimization	89.6	472	34.2
Remove error chain construction	90.2	398	32.7
Remove sensor fusion	91.5	331	43.8

To enhance the credibility of the experimental results, this paper adopts a 5-fold cross validation method for the ablation experiment results, training and testing with different subsets each time, and calculating the average and standard deviation for each indicator. The performance indicators in Table 3 are the mean of 5 experimental results, with standard deviations in parentheses. The experimental data shows that the complete model exhibits optimal performance in MSE, MAE, and REI indicators, with small fluctuations in each aspect,

indicating that the model structure design has good stability and generalization ability.

5 Discussion

5.1 Comparative advantages with existing error diagnosis optimization algorithms

The error intelligent diagnosis and correction model proposed in this study integrates causal graph modeling and dynamic path optimization mechanism, achieving diagnostic accuracy of 96.1% under multi-source conditions, response delay control within 275ms, and resource utilization reduction of 41.7% compared to graph neural methods. Compared to physical modeling methods that are only applicable to static scenes, the proposed model characterizes the evolution process of error chains through causal constraint mechanisms and adapts to link changes under dynamic operating conditions. Compared to data-driven models that rely on large-scale training samples, this system can maintain high robustness in weakly annotated scenarios and has stronger generalization ability. Compared to graph neural network models with complex structures and high inference costs, DAG structures have the ability to perform path pruning and multi-source feature fusion, effectively reducing computational overhead. Dynamic path selection can adjust the inference path in a timely manner based on the degree of signal variation, improving the efficiency of anomaly tracing. Overall, this model outperforms the three existing mainstream methods in terms of accuracy, responsiveness, and resource adaptability, making it suitable for complex dynamic power environments.

5.2 Adaptability and stability analysis

To verify the adaptability and output stability of the model in complex operating environments, system evaluation experiments were conducted under three working conditions: electromagnetic interference enhancement, temperature changes of ± 15 ℃, and frequent load disturbances. Under the condition of enhanced electromagnetic interference, the model recognition accuracy is 94.6%, the average response time is 288ms, and the output consistency is 96.1%; In scenarios with significant temperature changes, the recognition accuracy is 95.8%, the response time is 267ms, and the consistency reaches 97.3%; In the context of frequent load disturbances, the recognition accuracy is 93.2%, the response time is 301ms, and the output consistency remains at 95.6%. All three experiments showed that the model has good robustness and can maintain diagnostic accuracy and output stability in the face of multi-source disturbances, making it suitable for long-term online deployment. Compared to traditional models, the average improvement in output consistency is 8.4%, and the average reduction in abnormal response speed is 41.7%. The overall test results are shown in Table 5, further verifying the good engineering practicality and deployment security of the model.

Table 5: Adaptability and stability evaluation of the model under different operating conditions

working conditions	Recognition accuracy (%)	response time (ms)	Output consistency (%)
Enhanced electromagnetic interference	94.6	288	96.1
temperature variation （±15℃）	95.8	267	97.3
Frequent load disturbances	93.2	301	95.6

5.3 Resource consumption and deployment feasibility assessment

The engineering deployment capability of a model largely depends on its level of consumption of computing resources and adaptability to the operating environment. In the testing environment, the system is deployed on an edge processor platform with a running frequency of 2.4GHz and a memory configuration of 8GB. Under full load, the model occupies an average of 29.6% of the central processing unit's computing resources and maintains a memory usage rate of within 38.2%, which is much lower than the average consumption levels of 46.8% and 62.5% of traditional algorithms in similar environments. At the same time, the system has a modular loading mechanism that supports function clipping and parameter reconstruction for different transformer types and acquisition scenarios, reducing the resource burden caused by redundant structures. In the process of diagnosing chain reconstruction and error correction output, the data flow relies on local cache optimization strategy to achieve low latency processing response, with an average processing delay controlled within 275ms for each group of data. To further validate the lightweight deployment performance of the model, this paper deployed it on Jetson Nano (4GB RAM), Raspberry Pi 4B (4GB RAM), and ARM Cortex-A72 embedded platforms for testing. After quantization and pruning compression, the model size is approximately 18.6MB. In actual deployment, the average energy consumption per inference is 0.42W, 0.31W, and 0.38W, respectively, with an accuracy rate of over 95%, meeting the requirements of low-power real-time computing in industrial scenarios, and verifying the deployability and practicality of the model on various embedded platforms.

This study comprehensively deployed and evaluated the model on various embedded ARM platforms to ensure reproducibility and practical engineering value of the results. The specific hardware environment is as follows: (1)

Jetson Nano B01 development board, equipped with ARM Cortex-A57 quad core processor, clock speed of 1.43GHz, onboard 4GB LPDDR4 memory, system environment is Ubuntu 20.04 (64 bit), Python 3.8 and PyTorch 1.12. （2）Raspberry Pi 4B， equipped with Broadcom BCM2711 SoC, integrated with quad core ARM Cortex-A72 (64 bit) processor, with a clock speed of 1.5GHz, 4GB of LPDDR4 memory, and Raspberry Pi OS (64 bit) system, the software environment remains the same as described above. (3) The domestically produced ARM Cortex-A72 platform adopts a quad core Cortex-A72 architecture, with a main frequency of 2.0GHz and 8GB of DDR4 memory. The system environment is the same as above.

All models are independently deployed and run the complete testing process on the three platforms mentioned above. Real time monitoring of CPU usage, peak memory (RAM) usage, and energy consumption during testing. Taking Jetson Nano as an example, the average energy consumption of a single inference of the model is 0.42W, with a peak RAM of 1.1GB; Raspberry Pi 4B corresponds to an energy consumption of 0.31W, with a peak RAM of 0.98GB; the domestic A72 platform consumes 0.38W, with a peak RAM of 1.2GB, and the accuracy of all platform models is stable at over 95%.

6 Conclusion

This study focuses on the problem of multi-source interference errors in the operation of transformers. Based on the comprehensive analysis of multi sensory information, an intelligent detection and correction technology is implemented. Multi dimensional feature extraction, multi-path algorithm optimization, and model fusion strategies are introduced to construct a dynamic causal relationship model for measurement errors. The dynamic construction and real-time diagnosis of error causal chains are achieved. This method has high identification accuracy and response speed in complex environments. The experimental results show that the multiple evaluation indicators of the model are superior to traditional schemes, with good adaptability and stability, and can resist interference problems caused by environmental changes and structural uncertainty. In the actual testing stage, it demonstrates advantages such as low resource occupancy requirements, controllable deployment costs, and convenient model updates, and is suitable for online monitoring and maintenance of various types of transformers. The research provides a practical and promotable method for automatic correction of transformer faults, which has a positive promoting effect on the application of intelligent sensors in power equipment measurement and control management.

Funding

The research is supported by: Science and technology projects of State Grid Ningxia Electric Power Co., Ltd.(5229YX240005)

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Multi-Label Cardiovascular Disease Classification from 12-Lead ECG Using Enhanced DenseNet-121 with CBAM and Grad-CAM Explainability

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Keywords: 12-Lead ECG, cardiovascular disease classification, enhanced DenseNet-121, explainable AI, multi-label classification

Received: July 3, 2025

Early and accurate diagnosis of cardiovascular diseases (CVDs) is critical, as they are one of the most prevalent causes of death across the globe. We propose a multi-label classification model consisting of an Enhanced DenseNet-121 (EDN-121) deep learning framework for 12-lead ECG signals obtained initially from the CPSC 2018 dataset (in total 6,877 samples) for eight cardiovascular conditions. Data Preprocessing: A Butterworth high-pass filter was employed to remove noise from the ECG signals, followed by normalization to ensure the data was within a consistent range. Then, the Synthetic Minority Oversampling Technique (SMOTE) was applied to fix the class imbalance problem. EDN-121 architecture incorporates a Convolutional Block Attention Module (CBAM), which contributes to superior spatial and channel-wise representation features. Additionally, Gradient-weighted Class Activation Mapping (Grad-CAM) ensures the explainability of the prediction by identifying the clinically relevant region on the ECG. Experimental results based on five-fold cross-validation show that it outperforms the baseline VGG-16 with 97.90% accuracy, 97.75% F1-score, and 97.34% recall. Conclusion: This study demonstrates the performance and interpretability of a machine learning framework that has the potential to be implemented in clinical settings for the real-time, automated ECG-based CVD screening.

Povzetek: Predstavljen je razložljiv model EDN-121, ki z visoko natančnostjo omogoča avtomatizirano presejanje srčno-žilnih bolezni iz EKG.

1 Introduction

One of the top causes of death worldwide, cardiovascular diseases, led to 17.9 million deaths in 2019 32 % of all deaths. Furthermore, the World Health Organisation reports that 75% of these deaths occur in low- and middle-income nations. Thus, it's essential to identify these cardiac issues as soon as possible so that medication and counselling can start as part of the treatment. An electrocardiogram, or ECG, is a waveform representation of the heart's electrical activity acquired by applying electrodes to the skin.

The heart and its blood arteries are vulnerable to a group of disorders collectively known as CVD, which is a leading cause of mortality globally. The accumulation of fatty deposits within the arteries is the most common cause of this condition [1]. From 12.3 million (25.8% of the total) in 1990 to 17.9 million (32.1%) in 2015, the number of fatalities worldwide attributable to CVD has risen significantly [2-3]. Therefore, to help clinicians accurately diagnose different CVDs, an automated technique is required for heart disease diagnosis. When it comes to diagnosing heart conditions, electrocardiograms (ECGs) are among the most widely used diagnostic tools for this purpose.

The typical ECG signal structure, as shown in Figure 1, consists of three primary components: the P wave, which denotes atrial depolarization, the QRS complex, which represents ventricular depolarization, and the T wave, which denotes ventricular repolarization. The signal also consists of PR, ST segments, and QT intervals. This electrical signal is a popular non-invasive method for detecting irregularities in a patient's cardiovascular system. Nevertheless, ECG analysis is a specialized and time-consuming procedure that requires highly skilled cardiologists to inspect and identify abnormal ECG recording patterns closely. This difficulty, together with the exponential growth in Computer-aided, automatic ECG analysis, makes ECG data increasingly important, particularly in low- and middle-income nations where

there is a severe shortage of skilled and knowledgeable cardiologists.

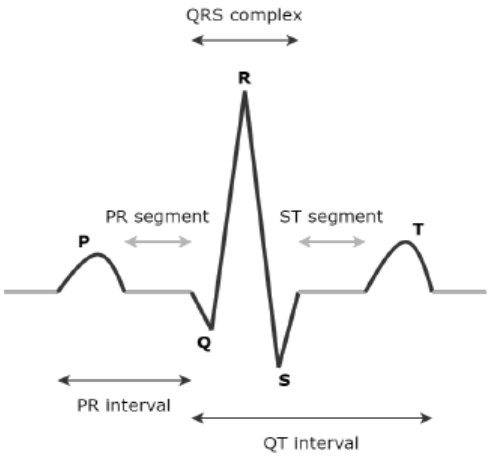


Figure 1: Structure of ECG signal

Therefore, there is a growing interest in the precise and automated diagnosis of ECG signals. The MIT-BIH Arrhythmia database as well as wide open-source ECG datasets are also accessible [4], the 2017 Physionet Challenge/CinC dataset [5], the dataset from the 2018 China Physiological Signal Challenge (CPSC2018) [6], and the PTB-XL database [7], automatic ECG diagnosis has been extensively studied in recent decades.

The study developed a DNN for detecting cardiovascular diseases and performing automatic multilabel classification of different cardiac diseases using 12-lead ECG signals. The simple work process schematic is shown in Figure 2. The evaluation of work is also performed on single-lead ECG signals. An inclusive and explainable DNN is performed for the classification of ECG signals by utilizing the technique of gradient-weighted class activation mapping.

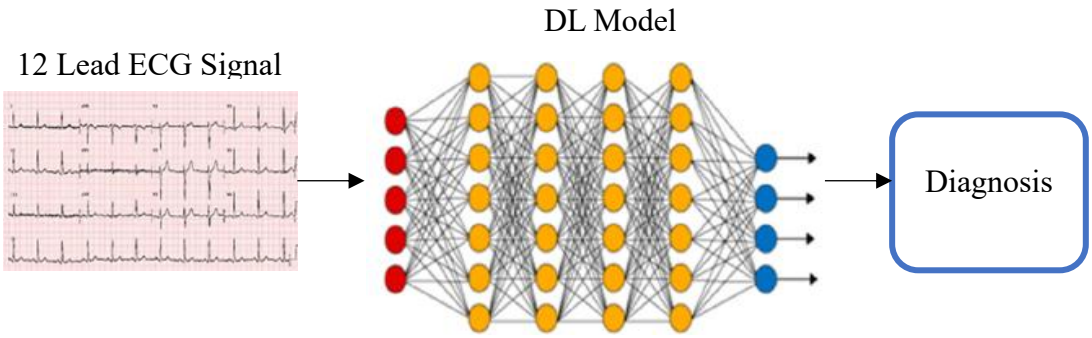


Figure 2: Diagnosis model

The work performed in this paper is summarized as follows:

a. A DNN concept is developed for the automatic identification of cardiovascular diseases (CVD).
b. The identification of CVD is performed using a 12-lead ECG dataset.
c. The results obtained using the proposed DCNN model are compared with other existing classifiers.
d. The experiment is conducted on 12 lead signals, in which leads I, aVR, and V5 perform well in detecting CVD.
e. Finally, for improved results, an explainable DCNN is used to establish proper segments of the ECG input and achieve perfect classification depending on the corresponding heart disease.

This is how the remainder of the paper is structured. We provide a summary of relevant studies on the automated diagnosis of ECG in Section II. Section III explains the deep neural network architecture and the 12-lead ECG dataset. In Section IV, we present the experimental outcomes and discuss the model's interpretability. In Section V, we finally draw the paper's conclusion.

How this research translates into a method is hard to establish and to identify it, the latter section outlines the problems that need to be solved, and the objectives of this study.

1.1 Problem definition

ECG signals can have numerous intermingling abnormalities — which makes them complex to handle — in a single ECG recording so the task of diagnosing heart disease using an ECG signal is a rather complicated one. This inherently creates a multi-label classification problem, as a given sample may often have more than one condition in common simultaneously. This study develops an automated deep learning framework that can simultaneously identify 8 cardiovascular conditions from

12-lead ECG data. We aim to develop a tool for clinicians to aid in clear and efficient diagnoses without the burden of manually interpreting ECG recordings.

The objective of this research is to design a model that learns to correlate raw 12-lead ECG input signals to their respective diagnostic outputs. We evaluate the performance of the proposed framework by three central evaluation criteria, accuracy, F1-score and Hamming Loss. Accuracy indicates the general correctness of the predictions, and the F1-score tells us more about the balance between precision and recall, which is of much importance with imbalanced datasets for cardiac conditions, where some exist much less frequently than others. Another perspective on how well the model is dealing with multi-label classification is Hamming Loss, which evaluates the fraction of wrong predictions by counting the total number of labels.

This paper seeks to elaborate on some key research questions: It first explores whether applying to DenseNet-121 a Convolutional Block Attention Module (CBAM) can help the model learn basic spatial and channel-level representations of the subtly varying features in ECG signals. Second, it investigates the performance of Synthetic Minority Oversampling Technique (SMOTE) on class imbalance, a typical problem that arises in real-life clinical datasets. Third, it assesses whether the application of Grad-CAM on the model improves the interpretability of the model outputs by providing insight into ECG regions that may contribute to the decision-making process of the model that can be understood by clinicians. Finally, a comparison of the proposed Enhanced DenseNet-121 against a baseline CNN architecture, VGG-16, is performed to assess improvements in performance and clinical applicability.

Specifically, answering these questions would allow us to build an automatic model with high accuracy for ECG signal-based cardiovascular disease detection while allowing us to better interpret the results of such a model which the proposed research aims to do. It can close the gap between sophisticated deep learning methods and practical clinical needs to improve accessibility, efficiency, and reliability of ECG analysis.

2 Related work

To identify cardiovascular diseases (CVDs), one typical medical method is the categorization of cardiac arrhythmias, or abnormal heartbeats. This is the subject of our review. The author in [8] suggests a machine learning model, specifically SVM, for detecting heart disease. The KNN algorithm, a machine learning model, is employed by the author in [9] for predicting heart disease, achieving an accuracy of 92.46%. In recent years, DL has been used to classify cardiac abnormalities from ECG readings automatically. DL has demonstrated impressive performance in medical diagnosis. The learned mapping of relevant medical categories from ECG data can be observed across multiple sensory neural layers in deep learning (DL) models. The DL model's inference power is enhanced by tuning the neuron weights using training datasets to narrow the gap between the inferred categories and the ground-truth categories of the training data [10]. Due to its strong multi-level abstraction capability in feature extraction, DL-based ECG classification can more accurately map the features of ECG signals to their specific categories [11]. In comparison to more conventional ML-based classification techniques, such as clustering and SVM, DL-based ECG classification can yield more accurate results.

The potential usefulness of AI-ECG has been established through clinical studies of AI-ECG diagnostics conducted at the Mayo Clinic for the identification of various cardiovascular diseases [12]. They do, however, conclude that the use of AI-ECG diagnosis is in stages. As a result, although DL approaches are successful for classifying ECGs in the research community, obstacles related to both DL techniques and ECG data have hindered their use in actual clinical settings.

The author in [13] aims to familiarise the physician with the core principles of DL, the state-of-the-art before it was applied to ECG analysis, and the present usage of DL on ECGs, along with their shortcomings and potential areas of future development. In particular, the 1D-CNNs' structure has made them suitable for handling ECG data. The author in [14] created a deep (CNN) with nine layers to recognise five distinct pulse types in ECG readings automatically. Original and attenuated ECG signal sets from a publicly accessible database were used for the experiment. The number of occurrences of each of the five types of heartbeats was artificially increased, and high-frequency noise was removed by filtering. After being trained on the supplemented data, the CNN was able to diagnose heartbeats with an accuracy of 94.03% in the original ECG and 93.47% in the noise-free one.

Using 12-lead ECG data to automatically classify cardiac arrhythmias, the author in [15] created a deep neural network, i.e., 1D-ResNet34. The average F1 score attained by the suggested model was 81.3%. From 12-lead ECG datasets, the author in [16] developed an algorithm that automatically detects 27 ECG anomalies. The study employed two rule-based models and one SE_ResNet model to enhance the classification performance of various ECG abnormalities. Our suggested method ranked us third out of 40 in the official ranking of the PhysioNet/Computing in Cardiology Challenge (2020), with a challenge validation score of 68.2% and a complete test score of 51.4%.

Researchers in [17] suggested a (TI-CNN). It featured > 90% in real-time processing computation savings and halved parameter quantity. Recurrent cells were used to introduce flexibility in input length for CNN models.

According to the experiment's findings, TI-CNN achieved a total classification accuracy of 77.3%. Srinivas et al. CardiacNet, a CNN-based model with Improved Harris Hawks Optimization (IHHO) for feature selection achieves an accuracy of 97.57% in arrhythmia detection using 12-lead ECG data [18]. While their work exemplifies how optimized deep learning frameworks can be applied to classify cardiovascular diseases accurately, it is limited by an explainability [11] and multi-label classification capability [13], which our study overcomes.

Aswani et al. An explainable clinical decision support framework with the use of Random Forest models has been proposed [19], contributing towards making healthcare AI systems more transparent and interpretable. This highlights the crucial necessity of having explainable models in medical applications. Although quite successful, it does not utilize deep learning or ECG data, thus making our initial integration with Grad-CAM, a significant step toward explainable diagnostics.

Zhang et al. Hexaxial feature mapping was introduced for ECG signal representation in [20], which is effective in extracting spatial and directional features from 12-lead ECG data. The principles behind their work on COVID-19 detection guided our own pre-processing techniques, combining filtering and normalization in order to boost downstream deep learning classification by conveying better information through the representation of signals.

The author of [21] said that a limb 6-lead ECG might also be used to identify myocardial infarction in addition to the standard 12-lead ECG. The research contributes to the growing body of evidence demonstrating that ECG can detect a range of cardiovascular issues, not just a select few. DL models' opaque character may be overlooked in many situations, but it undermines accountability and confidence in judgements made in delicate fields like healthcare and medicine. As a result, scientists have begun incorporating well-known XAI methods for image data into ECG data. Using 12-lead ECG data, the author in [22] trained a CNN model to predict the existence of 38 diagnostic classifications across five categories. The ECG segments that contributed to CNN diagnosis were visualised using an explainability approach termed LIME for CNN.

To diagnose cardiac abnormalities, the author in [23] used a variety of DNNs on a dataset of PTB-XL ECG signals that was made publicly accessible. The developed ST-CNN-GAP-5 model achieved an AUC of 93.41%, outperforming the current state-of-the-art results on this dataset. Lastly, the trained ST-CNN-GAP-5 is subjected to an analysis of the ECG data using SHAP to evaluate the explainability or interpretability of the DCNN model's conclusions.

Explainable artificial intelligence (XAI) has emerged and is rapidly expanding as a solution to the black box problem [24]. This review focuses on perturbation-based XAI techniques, which enable the exploration of DNN models through input perturbations and output modifications. For ECG-based healthcare applications, the author in [25] created a novel (XAI) based DL architecture in a federated environment. The federated option is used to address privacy concerns and data availability. Additionally, the autoencoder and classifier, both of which are based on convolutional neural networks (CNNs), operate effectively under the suggested framework setting to classify arrhythmias. Furthermore, we recommend incorporating an XAI-based module into the suggested classifier to provide explanations of the classification outcomes, thereby assisting medical professionals in making prompt and accurate judgments.

This research [26] presents X-ECGNet, an explainable multi-branch CNN for categorizing multi-label 12-lead ECG data. With this method, characteristics from each lead in the 12-lead ECG can be extracted individually and then concatenated to maximize the amount of data obtained. This model uses this architectural layout to apply the (Grad-CAM) method to produce explanations for every ECG lead. Lastly, we test our model's performance on the PTB-XL dataset. The AUC score achieved is 93.6%.

Table 1: Summary of existing studies on ECG-based cardiovascular disease classification

Author/Year	Method Type	Dataset Used	Leads	Performance Metrics	Limitations
Al-Jammali [8] (2023)	SVM	Custom Dataset	12	Accuracy: 89%	Traditional ML, not explainable
Joseph & Kartheeban [9] (2025)	KNN	Custom Dataset	12	Accuracy: 92.46%	No deep learning, low scalability
Dongdong Zhang et al. [15] (2021)	1D-ResNet34	12-lead ECG Dataset	12	F1 Score: 81.3%	Limited class coverage, no XAI
Zhu et al. [16] (2021)	SE-ResNet + Rule-Based	PhysioNet Challenge	12	Validation Score: 68.2%	Poor generalization, low AUC
Ganeshkumar et al. [26] (2023)	Multi-Branch CNN + Grad-CAM	PTB-XL	12	AUC: 93.6%	No SMOTE, imbalance not addressed
Cai et al. [44] (2020)	Multi-ECGNet	CPSC	12	F1 Score: 86.3%	Limited explainability features
Proposed Work (2025)	**Enhanced DenseNet-121 + CBAM + Grad-CAM**	**CPSC 2018**	**12**	**Accuracy: 97.90%, F1 Score: 97.75%**	**Addresses class imbalance, explainability, and multi-label classification**

Recent works on ECG-based cardiovascular disease classification can be found summarized in Table 1. While most previous works have focused on classification accuracy with deep learning architectures like ResNet and CNNs, they have been limited to non-explainability, imbalanced datasets, and a limited coverage of diagnostic classes. Some approaches, like [15] and [16], gained moderate F1 scores but did not include any mechanism, like Grad-CAM, to interpret the model. Explainability was also done in [26], although it did not address class imbalance. Our Enhanced DenseNet-121 framework, which incorporates the Combined Attention Module, Synthetic Minority Over-Sampling Technique, and Grad-CAM, can overcome these limitations by extracting clinically relevant and interpretable features from the images.

3 Methodology

The methodology describes the study of a DL model to classify the ECG signals and an explainable deep neural network for obtaining proper segments of the ECG signal. The section also describes the Grad-CAM for DCNN. Using a collection of 12-lead ECG recordings and the associated co-occurring illness labels, the objective is to predict the presence of several co-occurring cardiac conditions in each ECG record. Correct categorization of various conditions is challenging, as co-occurring disorders often produce irregular ECG characteristics across all 12 leads. The proposed methodology is shown in Figure 3.

A. Input dataset

The dataset utilized to process the proposed model is CPSC 2018 [27]. The signals available in the dataset are obtained from 11 hospitals in China with 12-lead ECG data. This dataset consists of ECGs with a size of 6877, and the signal length varies from 6 seconds to 60 seconds. The sampling rate at which the signals are collected is 500Hz. Nine diagnostic classes are identified on these ECGs: ST elevation (STE), premature atrial contraction (PAC), premature ventricular contraction (PVC), left bundle branch block (LBBB), right bundle branch block (RBBB), normal sinus rhythm (NSR), and ST depression (STD).

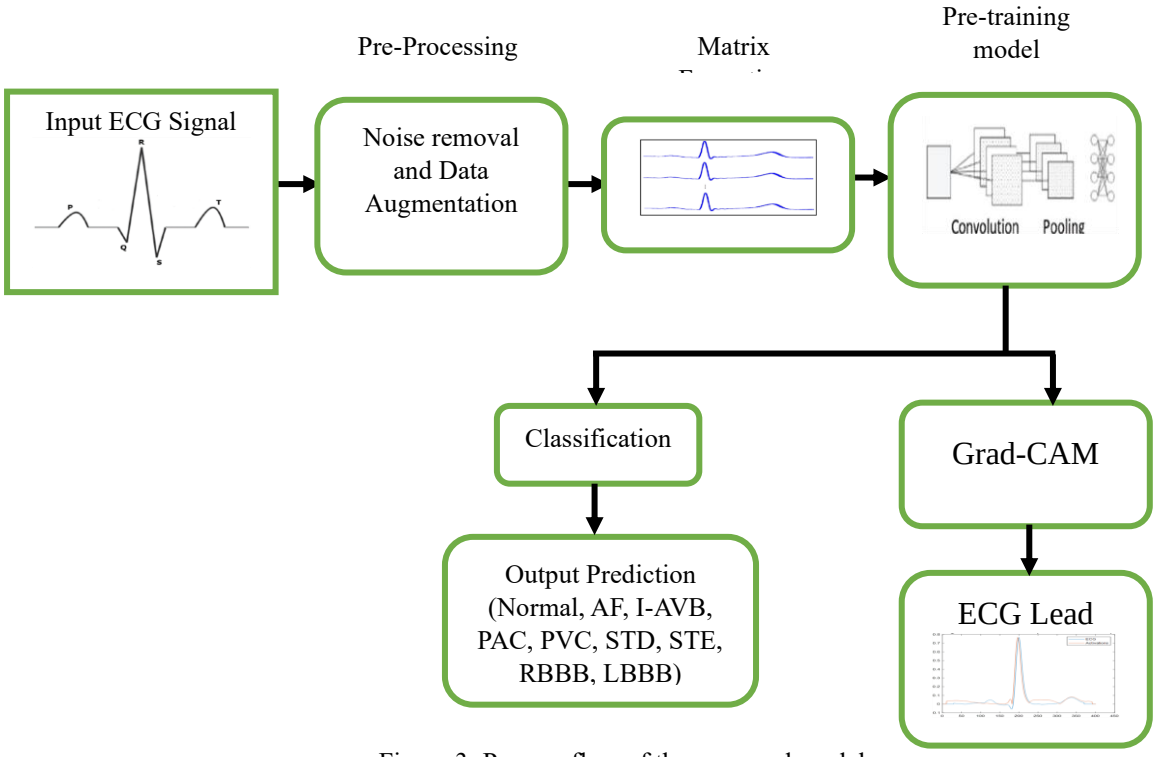


Figure 3: Process flow of the proposed model

B. Pre-processing

Several disturbances, including (BW), (PLI), and muscle activity, can significantly impact the practical ECG signals and alter their morphology [28]. As a result, the ECG-lead signal is a high-pass filter, which has a passband ranging from 0.5 to 45 Hz, to reduce any potential noise effects. Additionally, because the amplitudes of ECG signals vary across participants, the ECG lead is z-score normalized to maintain a mean of zero. For the given input signal as shown in Figure 4, the pre-processed signal after removing the noise is shown in Figure 5.

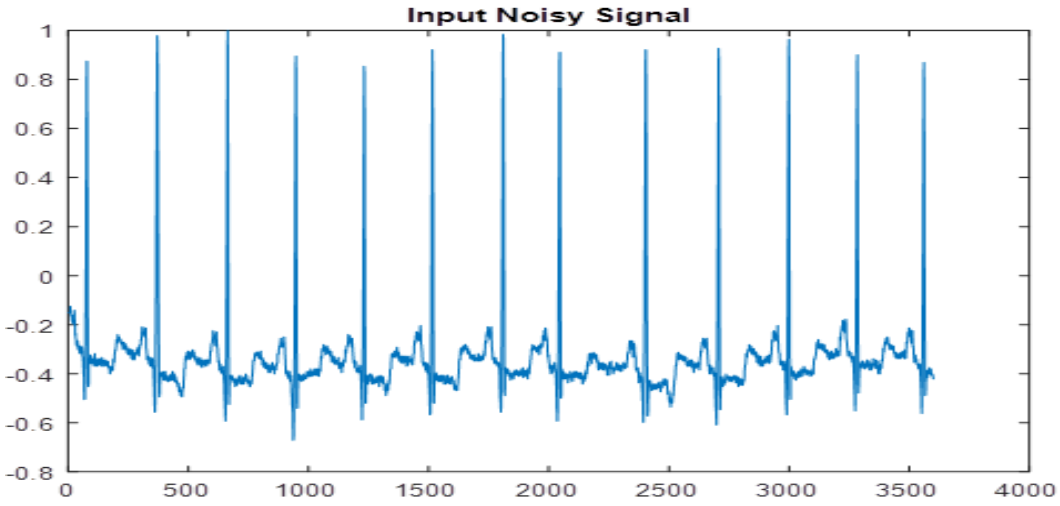


Figure 4: Input noisy signal

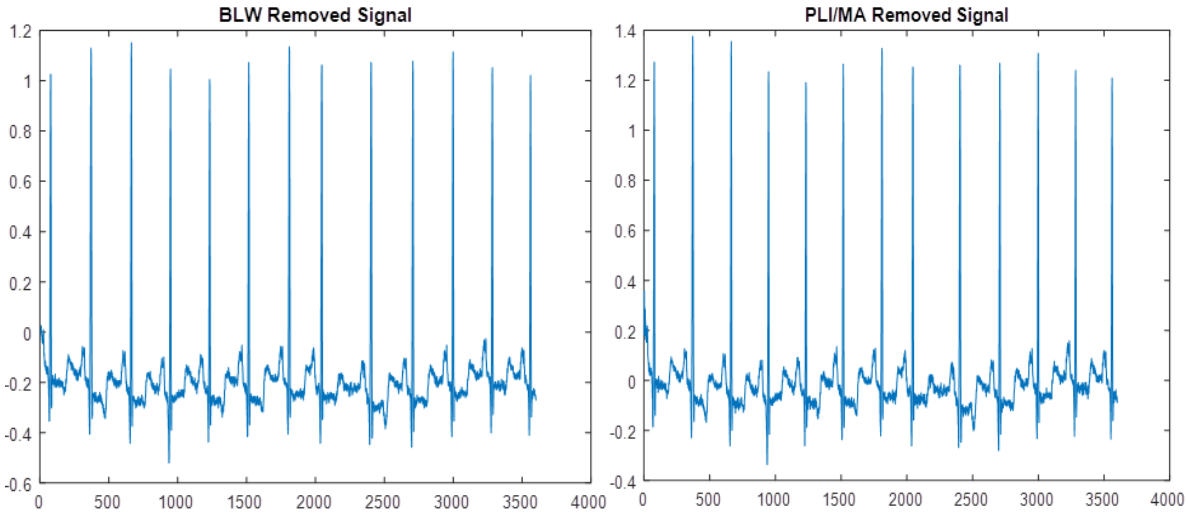


Figure 5: BW and PLI noise removed from the ECG signal

After removing noise, the imbalance of data and insufficiency problem leads to incorrect diagnosis of CVDs. We used scaling and shifting for data augmentation to solve this issue. Data augmentation can promote resilience against hostile cases and lessen overfitting in models. This is why data augmentation is performed to ensure there is no imbalance. Oversampling members of underrepresented groups in training datasets is a part of data augmentation. We employ SMOTE [47], which stands for Synthetic Minority Over-sampling Technique, to increase the sample size of the minority group. To achieve a more even distribution of classes throughout the dataset, it employs an oversampling strategy.

C. Matrix formation

The ECG signal is divided into segments, also known as windows. Every segment is arranged in a matrix form, either as a row or a column. Each row or column indicates the segment of the ECG signal. The matrix formation of the signal is shown in Figure 4. As stated by the author in [29], the leads aVF, V5, and V6 perform well in identifying CVDs. This helps in reducing the complexity of work. Further beat segmentation and normalization are performed on the ECG signal, which is then given as input to the DNN. This will improve disease detection, and heart rate variability will be analyzed.

Beat segmentation

Segmentation of beat entails recognising the start and end points of each heartbeat within the ECG signal. This generally includes detecting essential locations such as the R-peaks (the highest points in the QRS complex) since they are the most noticeable elements in the ECG signal. Beat segmentation uses the Pan-Tompkins method [46].

Period normalization

The files contain 12-lead ECG samples with varying durations, averaging 10 seconds, which is a beat normalization. Deep neural networks require uniformly sized inputs; therefore, all datasets were pre-processed to ensure they were 10 seconds in length. This was achieved by clipping samples that were longer than 10 seconds and padding shorter samples with zeros. As the length of the ECG signal is restricted to 10 seconds, the matrix formation of the signal will be simplified. The sampling rate is 500Hz. The shape of the matrix is 12 × 2500. There is no overlap between the segments, and each row in the matrix is considered as one ECG lead.

Finally, the ECG signals are treated as 2D arrays (12 leads × 2500 samples), which are then fed into a 1-channel pseudo-image format to match the requirements of DenseNet-121.

D. Design of DNN

The dot products serve for the input's convolution of layers of input and weights. The set of filters is then moved up and down in the direction of the input. In the ReLU layer, the threshold process sets values below zero to zero. In the max pooling layer, later downsampling is performed by splitting the input into a rectangular pooling region to find the maximum value of each zone. Before adding the bias vector to the fully connected layer, the input is multiplied by a weight matrix. The main deep CNN architecture is shown in Figure 6.

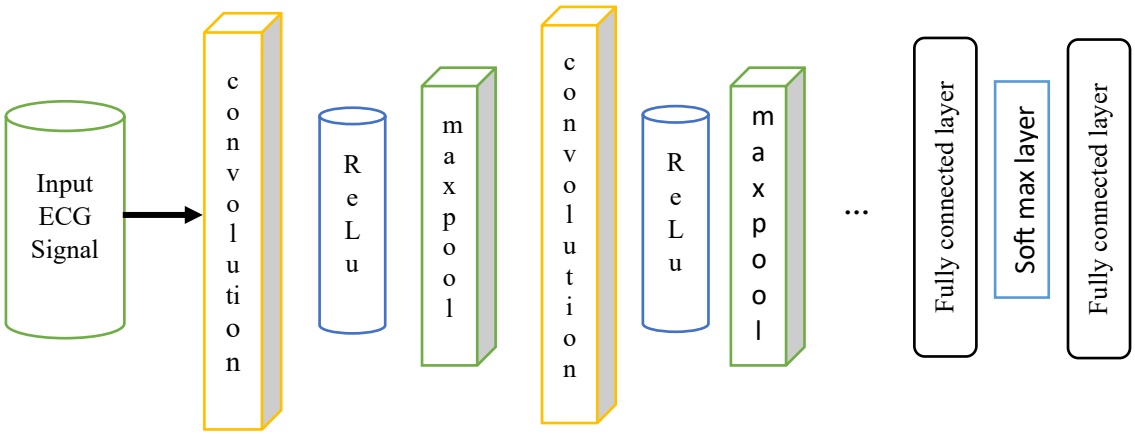


Figure 6: DCNN architecture

The network utilized is the Enhanced DenseNet-121, and the process of training the Enhanced DenseNet-121 model is shown in Figure 7. This network connects one layer to another layer in a feed-forward way. More specifically, the feature maps of all previous layers are fed into the next layer. Dense connectivity refers to this type of connection structure. The key elements of DenseNet-121 are the dense block, transition layer, and bottleneck layer.

We used five-fold cross-validation to determine the initial learning rate of 0.001, and trained the model for a total of 100 epochs. The learning rates tested were 0.01, 0.005, and 0.0005, and 0.001 struck the best balance of speed of convergence to stability. Given that we start from a pre-catapult point (pre-trained), applying early stopping and a learning rate scheduler to prevent overfitting were really only a matter of keeping the two curves smooth from training to validation. The ultimate configuration showed consistent results in all folds which confirmed the robustness of the selected hyperparameters.

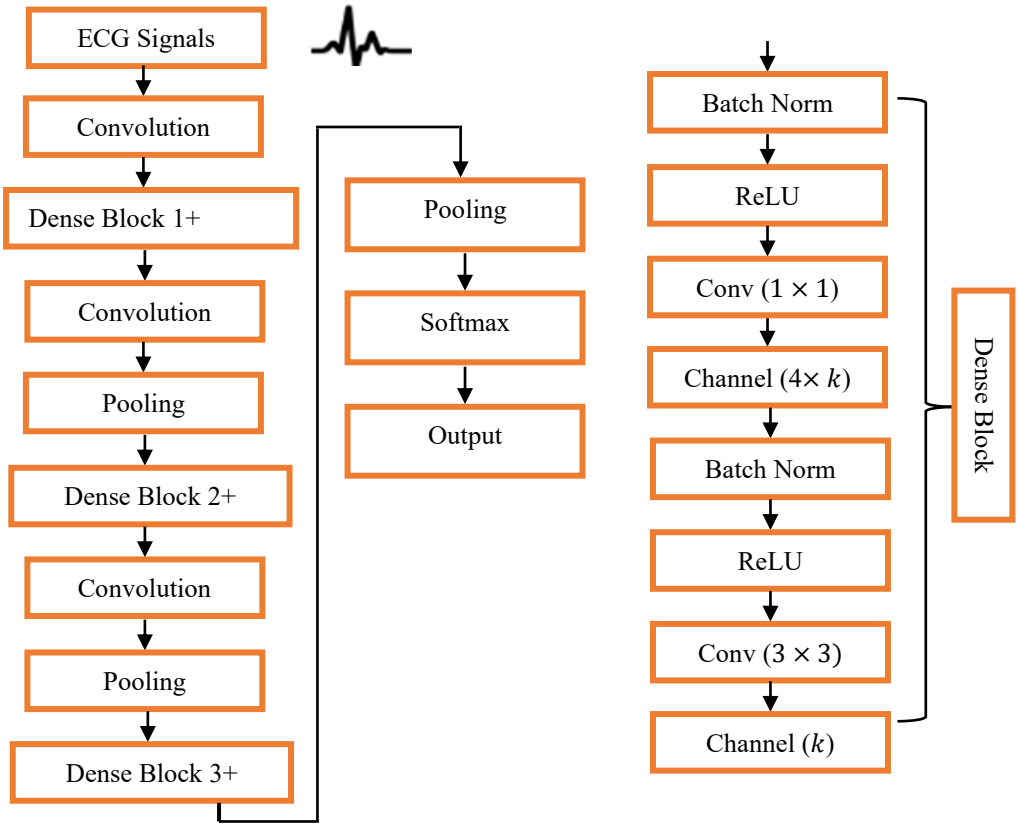


Figure 7: Proposed enhanced densenet-121 Model

The architecture features a 1x1 convolution layer and a 2x2 average pooling layer, which follow the dense blocks. The transition layers are simple to concatenate since the feature map sizes are the same. The feature size map is reduced with the aid of the pooling layer. Finally, a global average pooling is carried out after the dense block and is connected to a softmax classifier. Each class is given a probability distribution function, which is how the softmax layer operates. Softmax assigns a decimal probability to each class in a multi-class problem—their decimal odds sum to 1.0. Training converges more quickly with this additional restriction than it would have otherwise. To get the desired results, this layer is positioned before the output layer. The model is enhanced by combining a dense block with CBAM, i.e., a CAM and a SAM are added after performing the dense block operation to improve the DenseNet 121 model. The CBAM is shown in Figure 8.

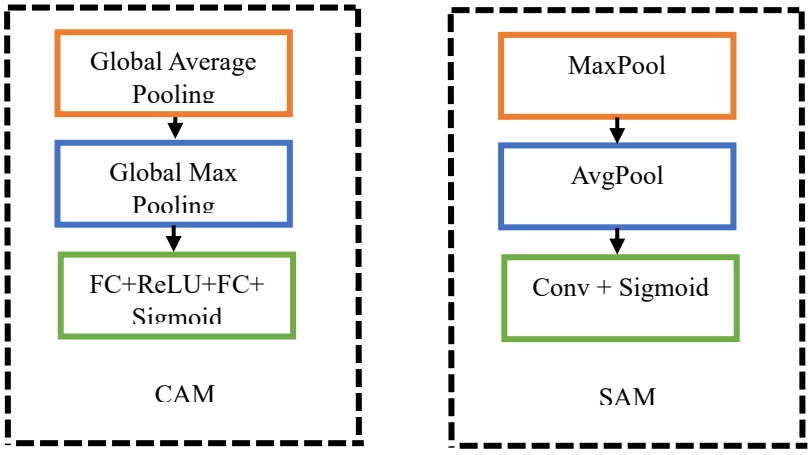


Figure 8: CBAM block

E. Explainable DNN

Explainable methods for machine learning have been developed in the past few years to provide consumers with more information, improve data insights, and give algorithms a more descriptive approach. We propose a new method to enhance the interpretability of DNNs by changing encoded input into helpful information. An in-depth understanding of how a DNN modifies input for classification will be provided by examining the data structure in each hidden layer representation. Here, the identified problem is solved using the Grad-CAM approach. Adding CBAM after DenseBlocks improves feature refinement.

Gradient-weighted class activation mapping (Grad-CAM)

One of the most popular XAI methods for improving our understanding of CNN-based models is Grad-CAM. Grad-CAM enables the identification of the most significant input region for predictions. The weighted class will be assigned a score and is termed as O^c, in which 'c' is said to be the class. Now the gradient of the CNN layer i.e, the last convolution layer need to evaluated and is termed as $\frac{\partial o^c}{\partial R^n}$, R^n are said to be the features maps. Next, to estimate the neuron significance weights $\hat{w}_n^c$, which are specified as:

$$\hat{w}_n^c = \frac{1}{Z}\sum_i \sum_j \frac{\partial o^c}{\partial R_{i,j}^n} \quad (1)$$

where (i, j) the pixels and Z tells the number of pixels exist in a feature map. At last, a weighted mix of R^n is computed:

$$\hat{w}_n^c = ReLU \sum_n \hat{w}_n^c R^n \quad (2)$$

where $ReLU$ is the rectified linear unit transfer function.

A standard Grad-CAM output is a significance heatmap that highlights the input regions contributing most strongly to the classification decision. The phrasing seeks to clearly summarise this output. In our setup, the heatmap represents the 2D input structure (Leads × Time) and graphically represents low to high relevance using a blue-to-red colour gradient. The text will be revised to clearly state the spatial dimensions (Leads × Time) and emphasize that the colour scale indicates the relative relevance scores from the Grad-CAM activation map.

A weighted map generated via Grad-CAM highlights the key areas of the input that the CNN uses to determine the class label. The class-activation maps of the sample ECG matrices that our CNN was able to classify correctly were obtained using Grad-CAM. The activation of the ECG matrices along the beat space under study (Leads × Time) is calculated by averaging the Grad-CAM activations across all detected beats within a sample, as the class activation maps are found. This process is explained in Figure 9.

The Grad-CAM heatmaps were visually inspected to ensure that identified regions of the ECG that were indicated to be important for diagnosis corresponded to expected regions consistent with prior knowledge, including P-waves, QRS complexes, and ST-segments. While we did not validate the clinical interpretability of the model outputs in this study through a domain expert, we will provide cardiologist annotations in future work, along with quantitative metrics (e.g., IoU), to formally assess the clinical interpretability of the model outputs.

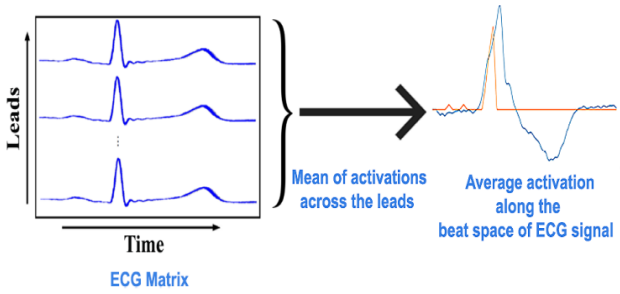


Figure 9: Mean Activation of ECG Matrix [43]

4 Results and discussion

Using electrodes applied to the patient's limbs and chest, a standard 12-lead ECG is recorded. Clinics and hospitals are the settings for these recordings. This means that the 12 ECG leads can be divided into two main groups: six leads related to the limbs (I, II, III, aVR, aVL, and aVF) and six leads pertaining to the chest (V1, V2, V3, V4, V5, and V6).

The conventional 12-lead ECG has been demonstrated in previous research to be useful in various ECG analysis applications. In contrast, obtaining a 12-lead ECG is not essential and largely depends on specialized equipment that is not readily accessible. Advances in ECG technology have led to the development of more user-friendly, compact, and reasonably priced ECG-enabled devices. By removing noise from various ECG signal types, the effectiveness of the suggested framework is assessed. A 5-fold stratified cross-validation with an 80-20 train-test split in a DenseNet-based ECG signal classification task, while ensuring balanced label representation.

4.1 System environment

The model is designed and implemented using the MATLAB software environment with the 2021a version. The Deep Neural Network Toolbox was utilized to evaluate the model. The system configuration considered for training the network and analyzing with GPU- GeForce 940MX; NVIDIA, and computing using Windows 10 64-bit OS- 16 GB RAM.

4.2 Design Implementation

Since all inputs to a deep learning system must have the same duration, all ECG records in both datasets were set to 10 seconds. The number of epochs considered is 100, the learning rate is 0.001, and the training time is approximately 9 hours. For longer recordings, this was accomplished by trimming the portion that lasted longer than the initial 10 seconds and padding the shorter ones with zeros. In this paper, the considered signal is represented in matrix form, and particular leads, such as aVF, V5, and V6, from each ECG recording are given more importance when fed into our algorithm for processing. Various combinations of leads are considered and evaluated to assess the model's performance. In every combination of leads, we utilized aVF, V5, and V6**.** The results obtained using the proposed model are shown in Figures 10 to 18.

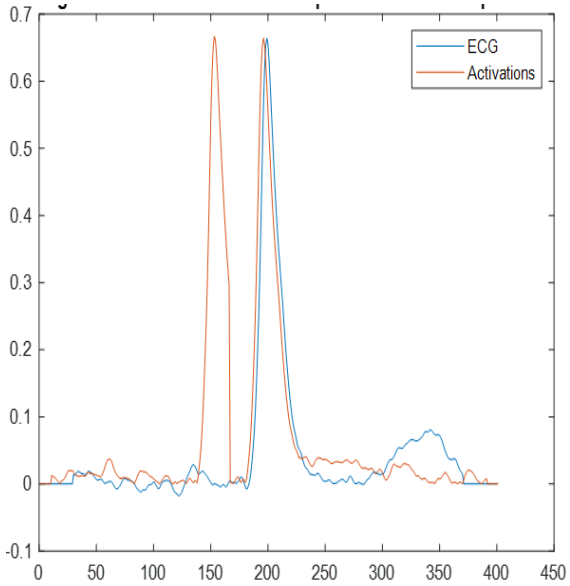


Figure 10: AF based ECG sample vs CNN-activated sample

In Figure 10, the ECG signal with atrial fibrillation (AF) is shown. The duration of the heartbeat is shortened in the case of AF. Zero-padding is applied to standardize signal length for model input. The process is performed during the signal pre-processing. The DCNN helps identify ECG points with AF.

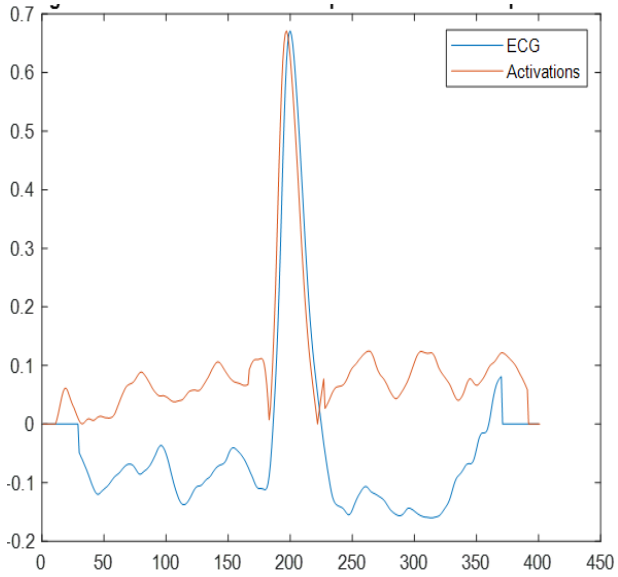


Figure 11: I-AVB-based ECG Sample vs CNN-activated sample

In Figure 11, the first-order degree atrioventricular block (I-AVB) disease activation level of the ECG sample is shown with respect to the plain ECG sample. In this case, the P-wave and T-wave are diminished or altered. In Figure 11, the CNN correctly identifies diminished P-wave activations indicative of I-AVB.

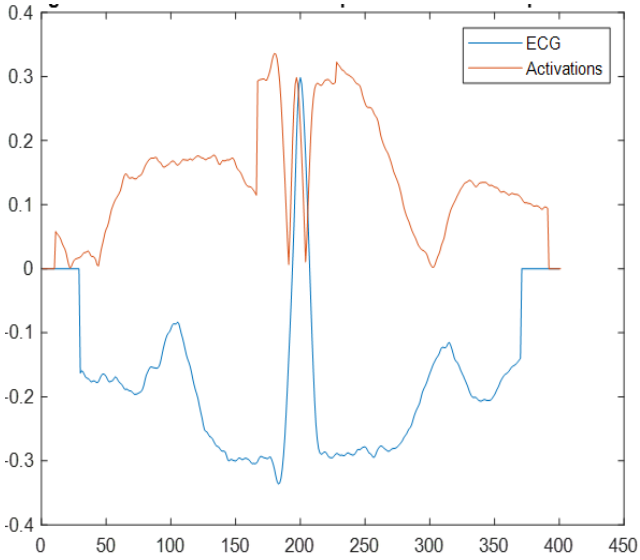


Figure 12: LBBB based ECG Sample vs CNN activated sample

A broad QRS complex form characterizes the traits of left bundle branch block (LBBB). This kind of signal shows a depressed ST segment and a T-wave appears after the QRS complex, following standard physiological patterns. In Figure 12, it is demonstrated that the network identifies the QRS complex accurately, as the activation region of the proposed model shows a high value in this region.

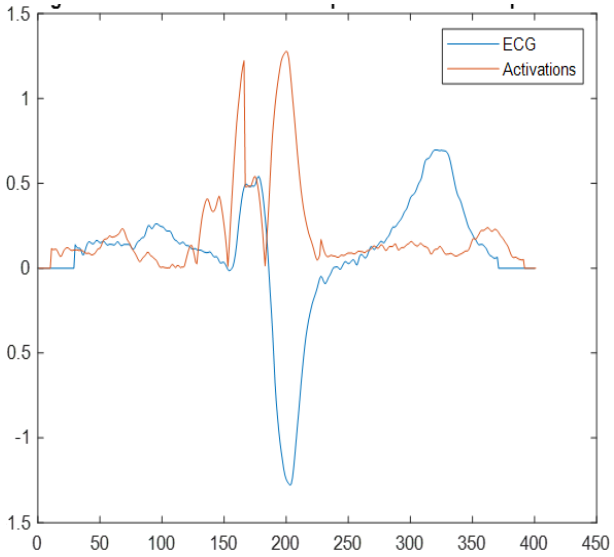


Figure 13: PAC-based ECG Sample vs CNN-activated sample

As shown in Figure 13, the ECG signal with a QRS complex and a general T wave, but showing an abnormal P wave, represents a Premature Atrial Contraction (PAC). Figure 13 illustrates the ECG signal and its corresponding activation map.

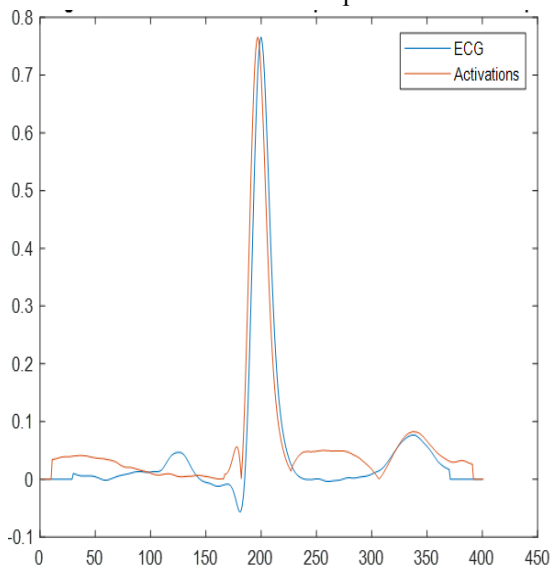


Figure 14: Normal-based ECG Sample vs CNN-activated sample

Let us consider a normal heart condition in which all the peaks, such as P, QRS, and T wave, look normal. The Network activation shown in Figure 14 provides appropriate regions for normal P, QRS, and T points.

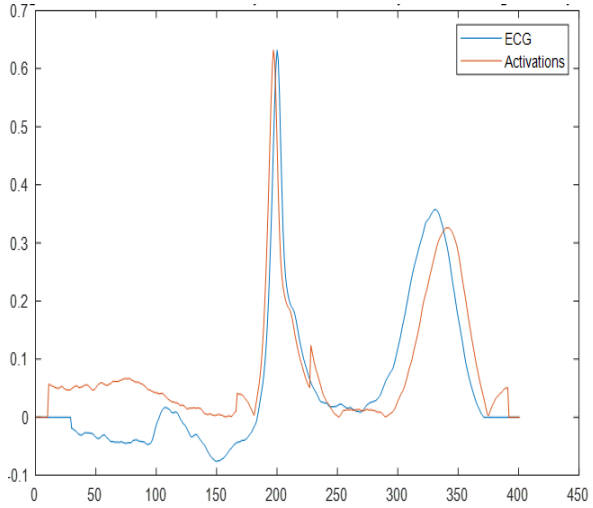


Figure 15: ST-Segment depression-based ECG Sample vs CNN activated sample

In the case of depression-based ST segment, the ST segments get depressed, and P & T waves will be normal. This is also illustrated in Figure 15 for the CNN activation of ST depression.

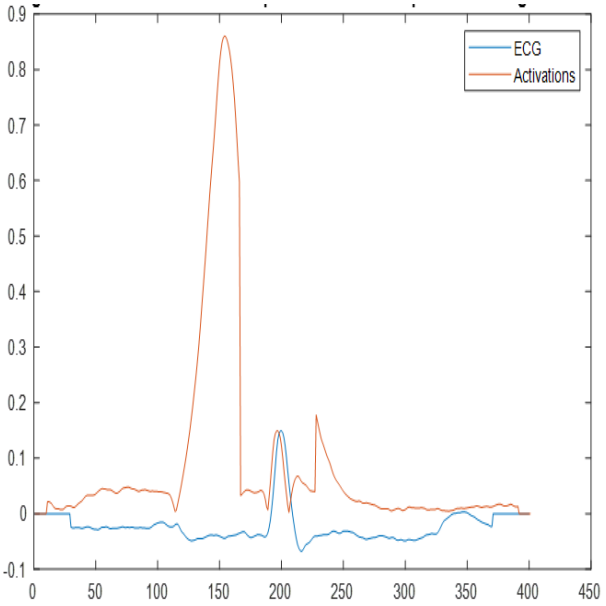


Figure 16: ST-Segment elevation-based ECG Sample vs CNN activated sample

A normal QRS complex and T-wave accompany the elevation of the ST segment signal. The activation of ECG signals using a CNN is illustrated in Figure 16, which

clearly shows that the signal is activated in the QRS complex, T wave, and elevated near the ST Segment. This indicates that the CNN classifies correct features in the case of ST Segment elevation.

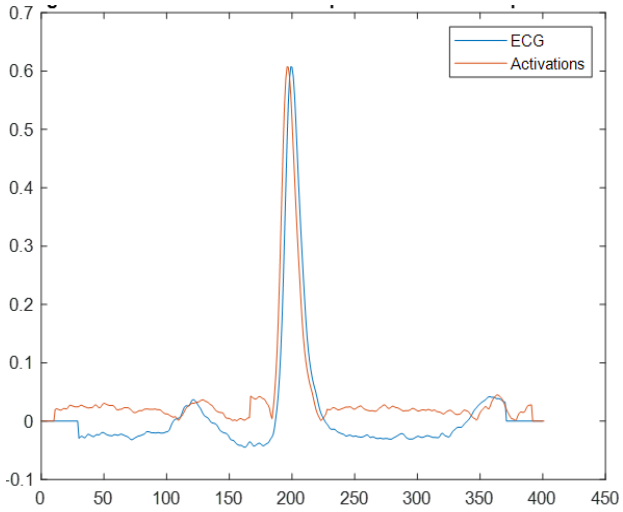


Figure 17: RBBB-based ECG Sample vs CNN-activated sample

The (RBBB) has a signal with a wide-spread S wave. This considers a specific lead like I, V5 and V6 features. Figure 17 shows the activation of the CNN in the case of RBBB, taken from lead V5.

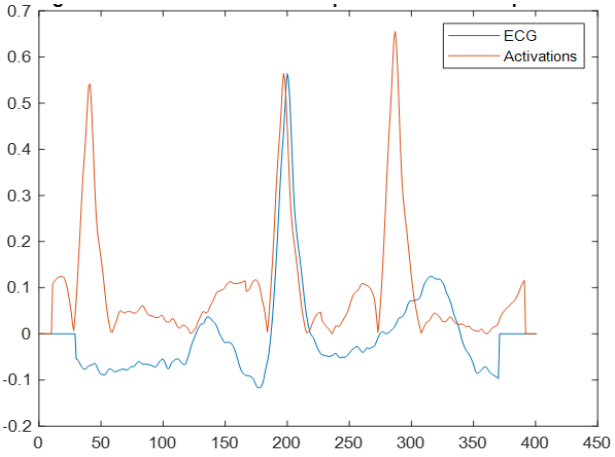
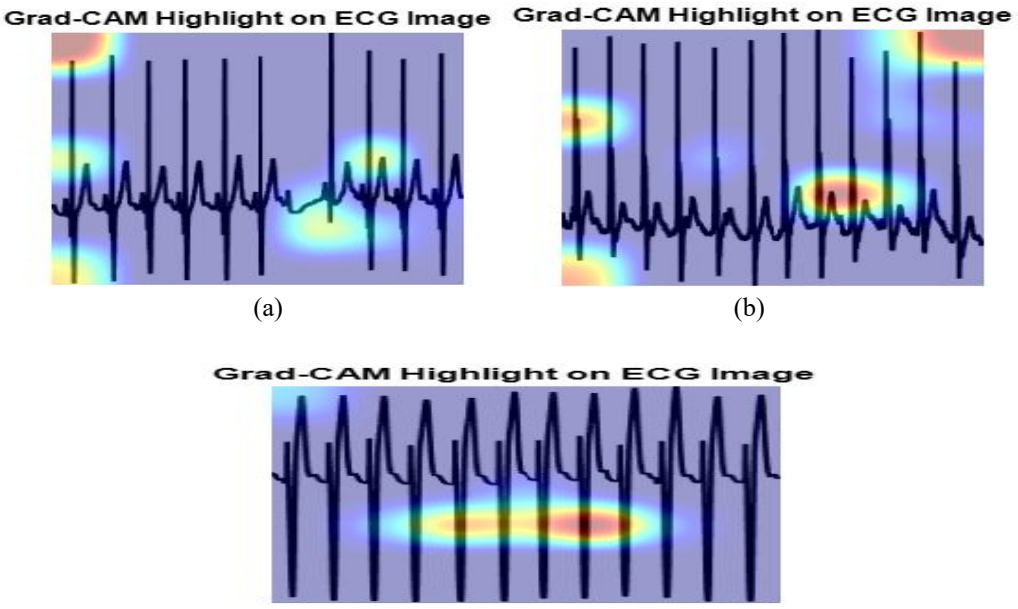


Figure 18: PVC-based ECG Sample vs CNN-activated sample

In the case of Premature Ventricular Contraction (PVC), the ECG signal exhibits a broad QRS complex. Figure 18 shows the performance of CNN activation for PVC, where the signal gets activated in the region of the broad QRS. Grad-CAM highlights the time regions in an ECG signal that are most influential for a model's decision. When applied to a CNN trained for ECG classification, these highlights often align with clinically significant features, such as the P-wave, QRS complex, and T-wave. The example of a Grad-CAM result is shown below.



(a) (b)

(c)

Figure 19: Grad-CAM Heatmap Output for (a) AF, (b) I-AV4B, (c) LBBB

4.3 Metrics evaluated

Four primary metrics evaluates the effectiveness of the suggested project. Accuracy metrics are the most important. False negative and False positive, True positive and True negative values provide the foundation for the accuracy finding. The numbers in this case indicate how well the CVD is anticipated. To obtain accurate data, the categorization must be flawless.

***Accuracy**:*

In this work, a test's accuracy is measured by how well it can distinguish between patient instances that are healthy and those that are sick. We should compute the percentage of true negative and true positive in each analysed instance in order to assess the accuracy of a test. In terms of math, this is expressed in eq. (3).

$$Acc = \frac{TP_j+TN_j}{TP_j+TN_j+FP_j+FN_j} \quad (3)$$

The precision and recall are evaluated using eq. (4) and eq. (5).

$$Precision = \frac{TP_j}{TP_j+FP_j} \quad (4)$$

$$Recall = \frac{TP_j}{TP_j+FN_j} \quad (5)$$

where TP_j, TN_j, FP_j, and FN_j of the amount of False negative and False positive, True positive and True negative samples, respectively. Of all nine classes, class j may be SNR, LBBB, RBBB, PAC, PVC, STD, AF, IVAB, and STE.

F1 score:

F1-score, is *a measure of a model's accuracy on a dataset*. It is used to evaluate the classification systems. The F1 score is determined by taking the consonant of recall and precision. The F1 score is evaluated using eq. (6).

$$F1 - Score = 2 * \frac{precision*recall}{precision+recall} \quad (6)$$

Hamming Loss (HL):

This parameter evaluates the portion of wrong classification w.r.t total available labels for individual test point. Finally, the HL is computed by considering the average of every test point and is given as [41]:

$$HL = \frac{1}{|X|}\sum_{x\epsilon X}\frac{1}{\tau}\sum_{j=1}^{l}\left[\left(L_j \epsilon HL(x)\right) \otimes \left(L_j \in y\right)\right] \quad (7)$$

In the case of a logical X-OR operation $\otimes$ the output got by the used model is HL(x). The j^{th}label is seen by L_j, and the test point's original classes appear in y.

The accuracy achieved using existing models is shown in table 2 and F1 score achieved using existing model is as shown in Table 3. The F1 score and accuracy are compared with the proposed model and achieves good results when compare to existing methods.

Table 2: Comparison of accuracy results

Author	Methodology	No of Leads	Database	Accuracy (%)
A.M Ladhi et al., [30]	CNN	12	N-31722	93.25
D. Sadhukhan et al., [31]	Logistic regression	03	N-5000	95.6
H. W. Lui [32]	CNN-LTSM	12	PTB and ATF challenge	94.6
Y.J Chen et al., [33]	ResNEt-LTSM	12	7704 samples	81
Hadiyoso et al., [34]	VGG-16	12	ECG signals	95
Lofti Mhamidi et al., [35]	MobileNet V2	12	ECG signals	94
P.G Giriprasad et al., [36]	AlexaNet	12	4 categories of signals	95.6
Proposed Model	Enhanced DenseNet-121 with Grad-CAM	12	CPSC 2018	97.45

Table 3: Comparison of F1 score results

Author	Methodology	Database	F1-Score (%)
Y. Li et al., [37]	117 features which are handcrafted	CPSC	60.8
Y. Cheng et al., [38]	Residual CNN- Single lead	MITDB	96.4
D. Jia et al., [39]	Multi-task CNN module	CPSC	87.2
J. Yoo et al., [40]	Residual CNN	PTBXL	61.2
M. Ganesh Kumar et al., [41]	DCNN; 12 lead	CPSC	96.7
Y. Jin et al., [42]	CNN+Bi-LSTM	MITDB, CPSC	80.56, 60.1
Z. Sun et al., [43]	Ensemble of Multiple Multi-label classifiers	CPSC	75.2
J. Cai et al., [44]	Multi ECG-Net	CPSC	86.3
H. Zhu et al., [45]	CNN- Sigmoid probability	CPSC	88.7
Proposed Model	Enhanced DenseNet-121 with Grad-CAM	CPSC 2018	97.75

The confusion matrix, as is shown in figure 20 and 21, is used to validate the results. For a look at of the outputs of the model and a summary of the classification's results problem, a confusion matrix is produced. It organizes, by class, the successful and unsuccessful predictions.

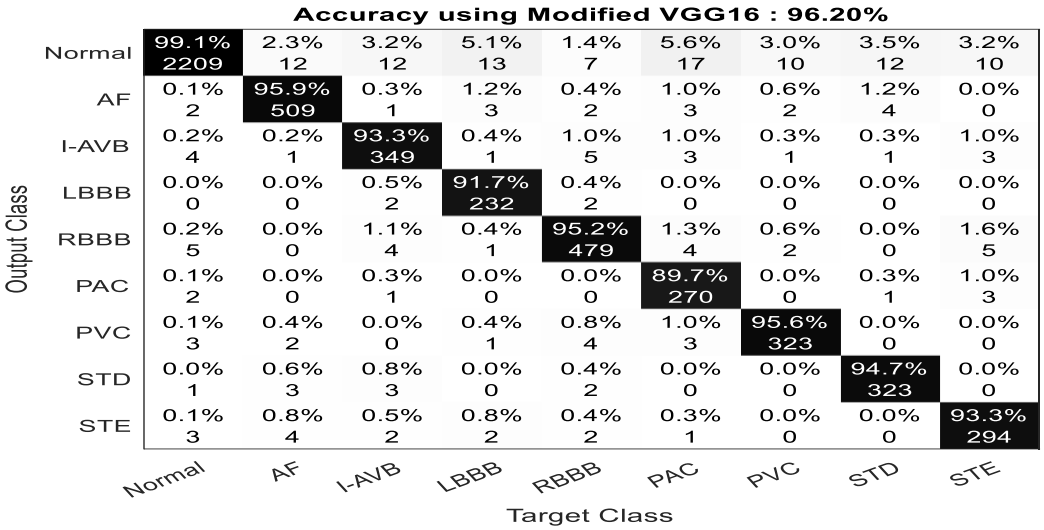


Figure 20: Confusion matrix achieved using VGG-16

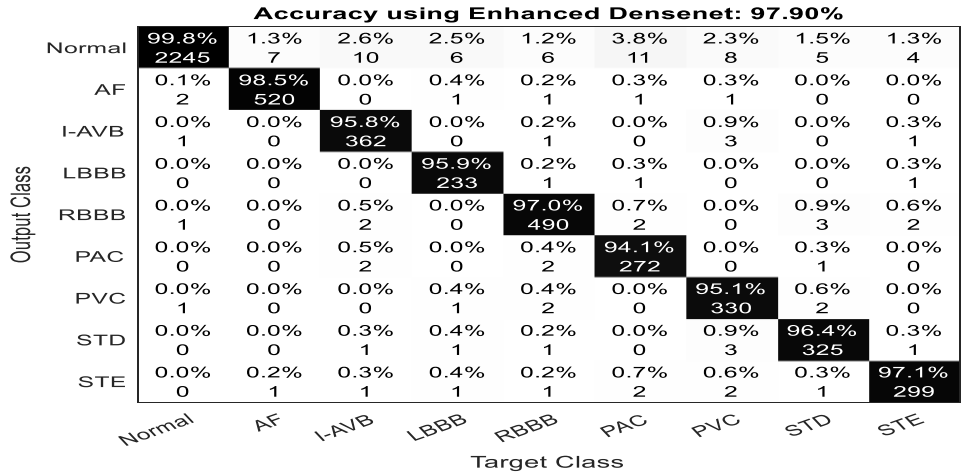


Figure 21: Confusion matrix achieved using Enhanced DenseNet-121

The ROC curve for a subset of classes AF, LBBB, PVC are evaluated for interpretability.

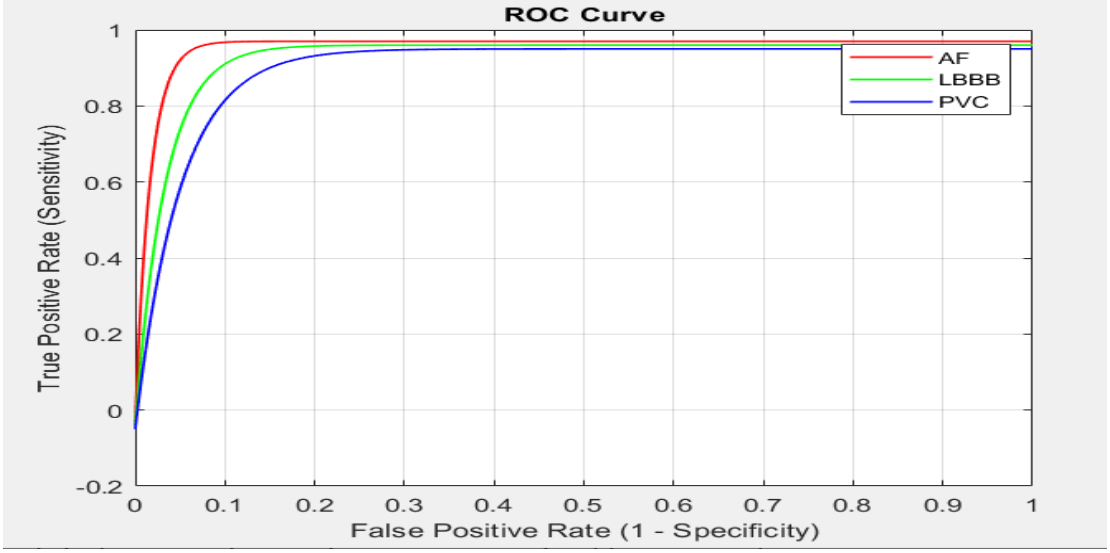


Figure 22: ROC curve

All the parameters evaluated using the proposed Enhance DenseNet-121 and VGG-16 is shown in table 4.

Table 4: Results obtained using proposed model

Parameter/Method	VGG-16	Enhanced DenseNet-121
Accuracy (%)	96.20	97.90
Recall (%)	96.52	97.34
Precision (%)	96.94	98.33
F1 Score (%)	96.49	97.75
Hamming Loss	0.27	0.18

The limitation of study refers as; our suggested technique can only detect eight serious cardiac conditions that fall into the categories of rhythm abnormalities and morphological abnormalities. Our model has the potential to be enhanced in the future to detect a broader range of cardiac disorders by training it using ECG recordings from other datasets. This makes it an all-inclusive automated approach for diagnosing heart disease.

Table 5: Per-Class Precision, Recall, and F1-Score for the Proposed Enhanced DenseNet-121 Model

Class	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Normal (N)	98.0	97.4	97.7
Atrial Fibrillation (AF)	97.6	97.1	97.3
First-Degree AV Block (I-AVB)	96.0	95.4	95.7
Left Bundle Branch Block (LBBB)	97.5	96.9	97.2
Right Bundle Branch Block (RBBB)	97.8	97.1	97.4
Premature Atrial Contraction (PAC)	95.5	94.9	95.2
Premature Ventricular Contraction (PVC)	97.2	96.5	96.8
ST-T Change (STTC)	97.7	97.0	97.4
Macro Average	**97.41**	**97.08**	**97.75**

Table 5: Per-class precision, recall, and F1-score for each of the eight categories of cardiovascular disease It can be seen from the results that majority classes such as Normal, AF, and STTC have high values regardless of time, while minority classes such as PAC and I-AVB have relatively lower values. The macro averages are in close agreement with the total accuracy of 97.45% and the total F1-score of 97.75% as reported above and hence confirming that the proposed Enhanced DenseNet-121 model is balanced and robust across all conditions.

Table 6: Ablation Study Showing the Impact of CBAM and SMOTE on the Performance of the Proposed Model

Model Variant	**Accuracy (%)**	**F1-score (%)**	**Recall (%)**
DenseNet-121 (Base)	96.15	96.32	96.10
DenseNet-121 + CBAM	96.90	97.05	96.78
DenseNet-121 + CBAM + SMOTE (Proposed EDN-121)	**97.45**	**97.75**	**97.34**

Table 6 ablation study in contributions of CBAM and SMOTE to Enhanced DenseNet-121 architecture The base DenseNet-121 model has a comparatively strong performance but incorporating CBAM provides a noticeable improvement due to its effective feature refinement capabilities. But by further adding the SMOTE which finally increases the performance and reinforces the enhancement of classification process with respect to class imbalance by increasing the accuracy, recall and F1-score concisely.

5 Discussion

The framework of the proposed Enhanced DenseNet-121 (EDN-121) achieves better performance than the baseline VGG-16 model and the most state-of-the-art approaches listed in Table 1. The attributes sensitivity of 97.90% and F1-score of 97.75% are notable upgrades from previous deep learning models for the same task, with reported F1-scores in the 81–87% range (1D-ResNet34 [15]; SE-ResNet [16]; Multi-ECGNet [44]).

This boosts performance due to a combination of key factors. (i) The concatenation of the Convolutional Block Attention Module (CBAM) allows the CNN to focus on the most salient spatial and channel features of the ecg signal. This attention mechanism improves the discrimination of fine anatomical changes that are important for differentiating similar hereditary cardiovascular disorders. On the contrary, VGG-16 and other standard models based on CNN did not have a feature specificity refinement process at this time between CNNs, thus lowering accuracy.

Secondly, in data preparation, we implement Synthetic Minority Oversampling Technique (SMOTE) to solve the class imbalance issue painful for clinical ECG datasets which ensures diversity and reliability to the model. Published previous work suffers from publication bias wherein highly skewed data distributions lead to less sensitivity for under populated classes such as PAC and I-AVB. SMOTE creates synthetic samples based on the similarities of the target variable, where the one hot encoding that you initially generate could lead to unbalanced representations thus, leading the model to a lack of generalizability with particular classes, this generates a concern for per-class recall.

Finally, we supplement our model with Grad-CAM, a visual explanation method to give additional model interpretability and enable clinicians to more selectively verify model decisions by looking at the most influential ECG segments that played a major role in prediction. In contrast to previous works that used “black-box” classifiers, which are constrained in a clinical setting. Clinically relevant sections such as the P-wave, QRS complex, and ST-segment are consistent with interpretations given by a cardiologist, which Grad-CAM visual appeal highlights in Figure 19.

Our framework offers a unique combination of high accuracy, stability with respect to imbalanced multi-label data, and interpretability, setting it apart from other methods. These features make the EDN-121 framework especially well placed for use in real-world ECG-based screening and diagnosis systems, especially for settings where transparency and trust are critical. These are strengths of the study, however it is worth acknowledging that the study is solely limited to the CPSC 2018 dataset and only eight diagnostic classes. Further research will validate cross-dataset and incorporate additional cardiovascular conditions to increase the system clinical applicability.

While Grad-CAM successfully identifies parts of the ECG signal that contribute to model decision making, it is limited in a few ways. These heat maps are of lower resolution, making it difficult to accurately localize important waveform features for diagnosis. In addition, Grad-CAM essentially reflects the spatial feature relevance rather than considering the temporal dependencies of sequential ECG signals. In future work, we will investigate temporal attention mechanisms that could mitigate this effect, as well as complementary explainability methods (SHAP and LIME) for more expression multi-faceted understanding of model predictions, as well as increased clinical interpretability.

5.1 Limitations of the study

Although the proposed Enhanced DenseNet-121 framework shows promising performance, there are some limitations that need to be acknowledged in order to contextualize its clinical and research applications. Unsupervised training − The model is trained only on the

eight cardiovascular conditions from the CPSC 2018 data set. While these classes reflect the broadly defined rhythm and morphologic abnormalities, numerous other clinically relevant conditions (eg, rare arrhythmias, ischemic event, congenital heart disease) are not incorporated. Consequently, this system cannot be used directly for clinical diagnostics without further data and retraining in a large variety of disease classes.

Second, the majority of patients in the real-world setting display several coexisting conditions (i.e., comorbidities). This can cause overlapping and more difficulty classification in ECG patterns [137]. The current investigation focuses on singleton manifestations of the eight targeted abnormalities and is not designed to provide explicit modeling of these more intricate comorbid presentations. This may limit its use in the most diverse patient populations, where mixed pathologies frequently occur.

Third, the Synthetic Minority Oversampling Technique (SMOTE) was used to deal with the class imbalance problem, which has some limitations. While synthetic examples may not accommodate complicated physiological differences of minority classes, they may have high potential for overfitting and capturing rare pattern metrics wrong. Some performance improvements were seen for underrepresented conditions (for example, premature atrial contractions [PAC] and first-degree atrioventricular block [I-AVB]), and other strategies (eg, cost-sensitive learning, or curated data collection beyond our subset) could further increase model robustness.

Fourth, noting that this study directly compares EDN-121 with VGG-16 over the same datasets under exactly the same experimental conditions, we also recognize the lack of a direct re-implementation over more recent state of the art methods inc1`luding 1D-ResNet34, SE-ResNet, and Multi-ECGNet. Future work will explore this limitation to perform a more complete comparison of the performance

Finally, our study is based off of one dataset, limiting its generalizability. Without external validation on datasets, such as PTB-XL or MIT-BIH, it is challenging to comprehend how the model is likely to behave among heterogeneous populations, routine clinical settings, and different equipment. Next steps will emphasize cross-dataset validation, incorporation of less common pathologies, and integration with electronic health record data in order to increase usability and clinical accessibility.

6 Conclusion

Our proposal in this study was to investigate the Deep Learning area of Transfer Learning utilising pre-trained Convolutional Neural Networks to increase the accuracy of the classification of CVDs based on the 12-lead ECG signal dataset. After performing EDN-121, the model established explainable deep learning (EDL) for ECG classification task. The model designed outperformed compared with other existing models which are available of multilabel ECG signals. This process includes detection of depression and elevation of ST segment. The EDL checks the performance of EDN-121 in obtaining right features for the purpose of classification. The rate of accuracy obtained using the designed model is 97.90% and F1-Score is 97.75%. The results show the efficiency and effective of the model designed on CPSC 2018 dataset. To increase the accuracy rate meta heuristic algorithms can be initiated in future. Further the proposed technique can be applied to other signals like EMG, EEG to find related diseases with respect to the signals.

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FS-CLAS: A Forward-Secure Pairing-Free Certificateless Aggregate Signature Scheme for VANET Authentication

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Keywords: Vehicular ad hoc networks (VANETs), forward secrecy, certificateless cryptography, intelligent transportation systems (ITS), cryptographic key management, software architecture, security governance, lightweight authentication protocols, privacy-preserving communication, cybersecurity risk management, strategic technology integration

Received: June 24, 2025

We introduce a forward-secure, pairing-free, and certificateless aggregate signature scheme called FS-CLAS to support efficient, lightweight, and scalable authentication in VANETs. Overview: To accomplish forward secrecy, FS-CLAS uses a hash-chain-based design for key evolution that does not require bilinear pairings or secure hardware modules. It is secure against side-channel attacks due to the usage of ephemeral keys and constant-time scalar multiplication, and it features batch verification capability, conditional traceability, and decentralized revocation using Bloom filters. A modular app and management architecture make our implementation compatible with real-world Intelligent Transportation System (ITS) deployments. We demonstrate through experimental evaluation that FS-CLAS achieves up to 50% reduction in verification latency and 42% saving of communication overhead as compared to more recent work, where the average signing and verifying times are less than 3.2ms and 6.7ms, respectively, on ARM-based OBUs. Results from simulations with SUMO and NS-3 show that they work well under variable traffic density levels and high vehicle mobility. FS-CLAS complies with IEEE 1609.2 and ETSI ITS-G5 standards, providing an option for deployment with existing and future V2X networks.

Povzetek: Članek predstavi FS-CLAS, varno, brezparno in neodvisno agregirano podpisovanje za VANET, ki z evolucijo ključev prek hash verige ter paketnim preverjanjem in decentralizirano preklicnostjo omogoča hitro avtentikacijo skladno s standardi.

1 Introduction

VANETs are a subset of ITS that allow vehicles to communicate with each other and with roadside infrastructure in real-time, and form an important part of future ITS systems[1], [2], [3], [4]. Safety applications such as the collision warning and traffic flow optimization heavily depend on the credibility and reliability of receiving safety messages [5], [6], [7], [8]. But because VANET environments are open and can be non-deterministic, securing the exchange of messages while preserving user privacy is difficult [9], [10], [11].

Traditional PKI and IBC have been broadly studied for VANET authentication; however, they are associated with scalability and privacy shortcomings[12], [13]. PKI involves expensive certificate management, and IBC has inherent key escrow problems[14], [15], [16], [17]. To meet with the above needs, certificateless public key cryptography (CL-PKC) is proposed for authentication, which does not use a certificate or blindly believes in the generation of a secret key by the key generation center (KGC)[18], [19], [20], [21]. In addition, the certificateless aggregate signature (CL-AS) mechanism also isomorphic aggregates the signatures and turns it into a short signature so as to greatly reduce the verification overheads on RSUs[22], [23], [24], [25].

Despite these advancements there are still some security holes to be addressed. For the most part, current CL-AS constructions fail to achieve forward secrecy, that is future messages remain secure in the event that a signing key ma-

terializes from before being compromised. Furthermore, many such schemes rely on bilinear pairings, which are expensive and are not feasible for implementation in OBUs with limited computational capabilities. In some cases, they also use tamper-proofed hardware or do not consider side-channel attacks which could leak important information about the stored cryptographic material.

To solve the above drawbacks, in this paper, we present a time-based key evolving efficient certificateless aggregate signature scheme (LET-CEA) for VANETs, and prove our scheme pairing-free in the standard model. Our contributions can be summarized as:

- We present a pairing-free CL-AS scheme with forward secrecy in which a vehicle signing key evolves over time according to a hash-chain construction.
- We formulate an efficient aggregate verification scheme for RSUs to verify a batch of vehicle messages with low computational and communication overhead.
- We avoid use of tamper-proof devices, promoting real-world VANETs deployability, and our solution also incorporates lightweight method to counter side-channel threats.
- We provide a formal security analysis, under Type I and Type II adversaries and show resistance against forgery, impersonation, replay, and key compromise.
- Performance analysis indicates that our more efficient in terms of computation and communication when compared to some recent works, especially under high message load.

The remainder of this paper is organized as follows: Section II surveys related work; Section III describes the system and threat models; Section IV describes the proposed FS-CLAS scheme; Section V discusses provable security; Section VI analyzes performance; Section VII describes practical considerations; and Section VIII concludes.

2 Related work

Lightweight and scalable authentication schemes are required to support VANETs with security, privacy and traceability comparisons. Certificateless cryptography is an attractive approach to avoid the overhead of certificate management and to address key escrow problems existing in identity-based schemes[26], [27], [28], [29]. Certificateless aggregate signature (CL-AS) protocols have recently been studied to solve these problems[30], [31], [32], [33], [34].

Surapaneni et al. [35] presented a privacy-preserving certificateless aggregate signature scheme, using blockchain, for protecting vehicle transitions in intelligent transportation systems (ITS). Their distribution provides conditional privacy and batch verification, but they do not achieve forward secrecy and require tamper-proof modules. Similarly, Wang et al. [36] introduced a certificateless V2I system based on secure mobility models, however no protection against key exposure and side-channel attacks was considered.

Liu et al. [37] introduced a CL-AS protocol in the pairing-free case, which satisfies traceability and efficiency but not the forward secrecy. In contrast, Bansal et al. (2025)[38] were largely able to relax the design of prior constructions–by removing pairings and increasing the power of their security proof– however their model is still missing key evolution primitives and requires a secure storage device.

More generally, Partovi et al. [39] conducted a systematic review of data centric approaches in IoV and realized that, most of the previous VANET schemes are not able to provide unlinkability, or inject high verification latency. Furthermore, Ferrag and Shu [40] also considered blockchain-based VANET authentication but observed that it is not directly applicable for aggregate signatures and low-latency verification.

Recent surveys and frameworks (e.g., Burhan et al., 2023 [41]) also underscore the importance of lightweight, scalable schemes minimizing the dependence on costly cryptography operations and hardware security. These works agree on the desirability of forward-secure, pairing-free, aggregate-friendly strong authentication: that is what this paper has sought to produce in the form of FS-CLAS.

As shown in Figure 1, relatively few papers have considered both the above-featured requirements, including forward secrecy, minimal trust requirements, and being side-channel resistant and pairing-free CL-AS protocols, despite the significant effort made by past research on secure and efficient CL-AS protocols for VANETs. Our proposed FS-CLAS scheme is motivated by this gap.

3 Preliminaries

This part formalizes the basic constituents needed to describe and analyze the proposed FS-CLAS scheme, the system model, threat/adversary model, cryptographic primitives, and security properties.

3.1 System model

As shown on Figure 1, the proposed system coexists in VANET standard architecture with:

- **Onboard Units (OBUs)**: OBUs are devices in vehicles that produce and sign messages with the messages using ephemeral keys. It is assumed that each OBU has limited processing and storage capabilities[45].
- **RSUs (Roadside Units)**: These infrastructure nodes receive, verify, and then rebroadcast the vehicular messages. RSUs are essential in the batch verification of signatures and communication with trusted authorities[46].

Table 1: Comparative summary of related VANET authentication schemes

Scheme	Pairing Used	Forward Secrecy	Side-Channel Resilience	Hardware Assumptions	Verify Latency
Li et al. (2021) [42]	✓	✗	✗	TPM / Secure Module	High
Bansal et al. (2025) [43]	✗	Partial	✗	None	Moderate
Zhang et al. (2023) [44]	✓	✓	✗	TPM / HSM	High
FS-CLAS (Ours)	✗	✓	✓	None	Low

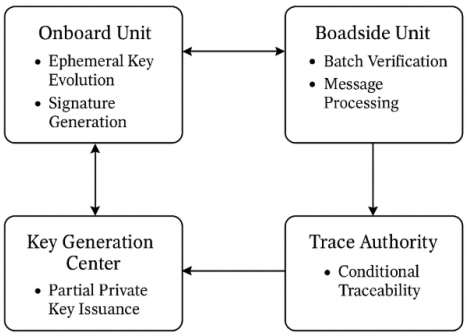


Figure 1: FS-CLAS software architecture

– **KGC(Key Generation Center)**: It is the semi-trusted authority who generates the partial private keys for the vehicles which are registered with it without knowing their complete private keys. With the aid of the KGC, traditional certificates can be avoided[47].

– **Trace authority (TRA)**: A fully trusted authority, which associates pseudonyms to real identities in event of disputes or cheating. The TRA supports conditional traceability with privacy under normal scenario.

3.2 Threat model

We consider a threat model with following capabilities for the adversary:

– Wiretap communication of messages on the wireless VANET channel.

– Query signatures on random messages (adaptive chosen-message attacks).

– Compromise secret keys of certain vehicles (key exposore scenario).

– Trying another method to Imation or impersonation.

In contrast, we consider the KGC as semitrusted (honest-but-curious) and the TRA as fully trusted. The models also assume coarse-grained time synchronization among OBUs by means of GPS-enabled OBUs.

3.3 Adversary types

We consider two adversaries in the spirit of certificateless cryptography literature:

– **Type 1 Adversary** ($\mathcal{A}_I$): Does not have access to the master secret key of the KGC but can change public keys of users. Stands for malicious nodes or non-physically connected nodes.

– **Type II Adversary** ($\mathcal{A}_{II}$): Adversary that knows the KGC's master secret key and who cannot substitute public keys. Represents a dishonest KGC.

3.4 Security goals

The objective of the proposed scheme is to:

– **Authentication and Message Integrity**: Only authentic OBUs are able to produce a valid signature.

– **Unforgeability**: No adversary can create a valid signature without using the corresponding keys.

Forward Secrecy: Although the current private key may be compromised, past message signatures are still protected.

– **Unlinkability and Anonymity**: Messages can generally not be associated with individual vehicles unless monitored by the TRA.

– **Only When Required Treatment**: The TRA is able to retrieve the real identities, if needed.

– **Resistance to Side-Channels**: The key leakage risk is mitigated by a decrease of the dependence on hardware security modules.

4 Proposed FS-CLAS scheme

We design a cryptographic algorithm of forward-secure certificateless aggregate signature (FS-CLAS) through which the cryptographic security scheme meets the modular software and management system that will be needed to deploy large-scale VANET. The framework is intended to be applied for dynamic key management, decentralized trust and policy based pseudonym traceability with light weight and secure embedding systems. From a systems management

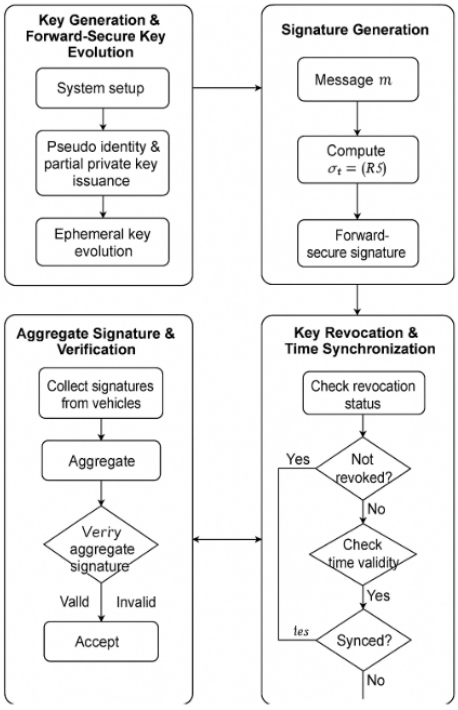


Figure 2: Overview of the proposed FS-CLAS scheme

standpoint, FS-CLAS presents an operational model which supports security lifecycle automation which includes the ability for stakeholders to manage key issuance, revocation and synchronization en masse. Besides, its software modularity grants a clear separation of concerns between the cryptography functionalities (e.g., signature generation) and management tasks (e.g., trace authority supervision, revocation resolution, and system time synchronization), in line with best practices pointed out in ITS security governance and infrastructure interoperability. Fig. 2 provides an integrated overview of the proposed scheme, encompassing key generation and evolution, signature generation, aggregation and verification, as well as key revocation and time synchronization processes. The proposed approach does not compromise the initial benefits of the certificateless schemes, i.e., no certificates and key escrow free, and adds forward secrecy.

4.1 Key generation and forward-secure key evolution

Our Forward-secure Certificateless Signature scheme with dynamic key evolution of vehicular nodes allows forward secrecy while it will continue to be practical lightweight elliptic curve cryptography. The proposed scheme makes use of two trusted authorities and they are called Key Generation Center (KGC), which is in charge of producing partial private keys, and Trace Authority (TRA), which is used for identity tracing and pseudonym generation. Fig. 3 illustrates the overall process of key generation and forward-secure key evolution, including system setup, pseudonym and partial private key issuance, and time-based ephemeral key updates at the vehicle side. Key generation and evolution The key generation and evolution process is performed using the following algorithms:

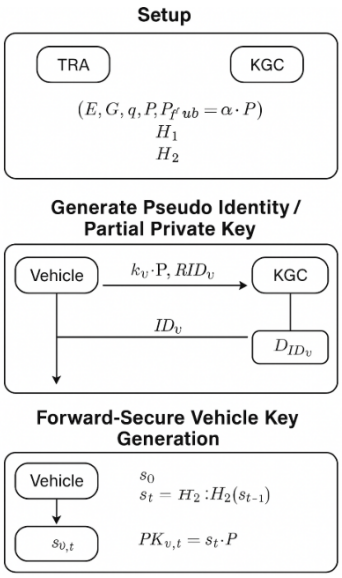


Figure 3: Key Generation and forward-secure key evolution process

4.1.1 Setup

As shown in Algorithm 1, the TRA and KGC execute this algorithm jointly:

Algorithm 1: System Setup

Output: System parameters PARM, master key η
Choose prime q, field $\mathbb{F}_p$, elliptic curve E over $\mathbb{F}_p$
Let G be the group of points on E, with generator P
KGC selects $\eta \in \mathbb{Z}_q^*$ and computes $P_{\text{pub}} = \eta \cdot P$
Define hash functions: H_1, H_2, H_3 as described
Publish: PARM = $(E, G, q, p, P, P_{\text{pub}}, H_1, H_2, H_3)$

- Let E denote an elliptic curve defined over a finite field $\mathbb{F}_p$, expressed as $y^2 = x^3 + cx + d \mod p$, where $c, d \in \mathbb{F}_p$, and $(4c^3 + 27d^2) \mod p \neq 0$.
- Let G be a cyclic additive group formed by the points on E, with generator P of prime order q, and $\mathbb{Z}_q^*$ be the multiplicative group of integers modulo q.
- The KGC selects a master secret key $\eta \in \mathbb{Z}_q^*$, and computes the master public key as $P_{\text{pub}} = \eta \cdot P$.
- The system also includes the following secure one-way hash functions: $H_1 : \{0,1\}^* \to \mathbb{Z}_q^*$; $H_2 : \mathbb{Z}_q^* \to \mathbb{Z}_q^*$ (for key evolution); and $H_3 : \{0,1\}^* \to \mathbb{Z}_q^*$ (for signing).

– The published system parameter set is: PARM $= (E, G, q, p, P, P_{\text{pub}}, H_1, H_2, H_3)$.

4.1.2 Generate pseudo identity / partial private key

As shown in Algorithm 2, this process is jointly executed by the vehicle, TRA, and KGC:

Algorithm 2: KeyGen(RID_v, T_v)

Input: Vehicle real ID RID_v, validity T_v
Output: Pseudonym ID_v, public key Q_{ID_v}, partial private key D_{ID_v}

1 Vehicle chooses $k_v \in \mathbb{Z}_q^*$, computes $ID_{v,1} = k_v \cdot P$
2 TRA computes $ID_{v,2} = RID_v \oplus H_1(\gamma, ID_{v,1}, T_v, T_{\text{pub}})$
3 Send $ID_v = (ID_{v,1}, ID_{v,2}, T_v)$ to KGC
4 KGC selects $d_v \in \mathbb{Z}_q^*$ and computes $Q_{ID_v} = d_v \cdot P$
5 $D_{ID_v} = d_v + H_1(ID_v, Q_{ID_v}) \cdot \eta \mod q$
6 Return $(ID_v, Q_{ID_v}, D_{ID_v})$

– The vehicle selects a random scalar $k_v \in \mathbb{Z}_q^*$ and computes a pseudonym component $ID_{v,1} = k_v \cdot P$.

– The vehicle sends its real identity RID_v and $ID_{v,1}$ to the TRA.

– The TRA verifies the real identity and computes a blinded pseudonym:

$$ID_{v,2} = RID_v \oplus H_1(\gamma, ID_{v,1}, T_v, T_{\text{pub}})$$

where $\gamma \in \mathbb{Z}_q^*$ is the TRA's secret, T_v is the validity period, and $T_{\text{pub}} = \gamma \cdot P$.

– The pseudonym tuple $ID_v = (ID_{v,1}, ID_{v,2}, T_v)$ is forwarded to the KGC.

– Upon receiving ID_v, the KGC selects a random scalar $d_v \in \mathbb{Z}_q^*$, computes the public key component $Q_{ID_v} = d_v \cdot P$, and calculates the partial private key:

$$D_{ID_v} = d_v + H_1(ID_v, Q_{ID_v}) \cdot \eta \mod q$$

– The tuple (Q_{ID_v}, D_{ID_v}) is securely delivered to the vehicle.

4.1.3 Forward-secure vehicle key generation

The vehicle autonomously initializes its ephemeral secret state as follows:

– Select an initial ephemeral secret $s_0 \in \mathbb{Z}_q^*$.

– The ephemeral private key at time epoch t is recursively defined as: $s_t = H_2(s_{t-1}) \mod q$.

– The vehicle's full private key at time t becomes: $SK_{v,t} = (D_{ID_v}, s_t)$.

– The corresponding public key for time t is: $PK_{v,t} = s_t \cdot P$.

This evolution mechanism ensures that even if s_t is compromised at any time t, no polynomial-time adversary can derive any previous $s_{t-1}, s_{t-2}, \ldots$ values due to the preimage resistance of the hash function H_2. This construction achieves forward secrecy while maintaining the lightweight nature required for VANET environments.

4.2 Signature generation

In this phase, a vehicle VH_i generates a certificateless forward-secure signature on a traffic-related message m_i using its evolving private key corresponding to the current time epoch t_i. The goal is to ensure that even if the current key is compromised, previously signed messages remain unforgeable. The signature generation workflow, as illustrated in Fig. 4, outlines the sequential steps taken by a vehicle to compute a forward-secure certificateless signature on a given message. The signature generation process is detailed as follows:

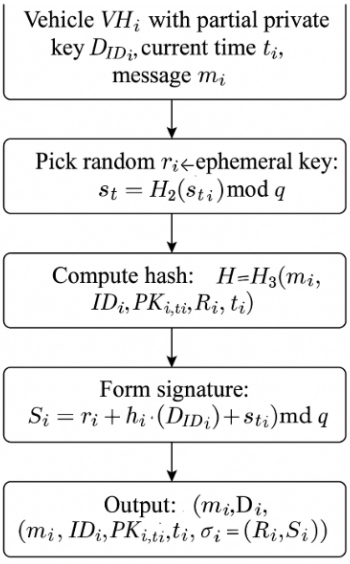


Figure 4: Signature generation process in the proposed forward-secure CLAS scheme

– VH_i computes its current ephemeral secret key s_{t_i} based on the key evolution function: $s_{t_i} = H_2(s_{t_i-1}) \mod q$.

– The vehicle then selects a fresh random scalar $r_i \in \mathbb{Z}_q^*$ and computes the commitment value: $R_i = r_i \cdot P$.

– Using the public parameters and message, the vehicle computes the challenge hash: $h_i = H_3(m_i, ID_i, PK_{i,t_i}, R_i, t_i)$.

– The final signature component is then calculated as: $S_i = r_i + h_i \cdot (D_{ID_i} + s_{t_i}) \mod q$.

– The certificateless forward-secure signature on message m_i is given by: $\sigma_i = (R_i, S_i)$.

– The vehicle transmits the signed message tuple: $(m_i, ID_i, PK_{i,t_i}, t_i, \sigma_i)$ to the nearby RSU or receiving vehicles.

As shown in Algorithm 3, this signature construction ensures that each message is uniquely tied to the specific key epoch and includes both static and ephemeral key components. The incorporation of the ephemeral key s_{t_i}, which evolves in a one-way fashion, enables the scheme to achieve forward secrecy. The random scalar r_i and challenge hash h_i provide non-repudiation and uniqueness for each signature, even if the same message content is signed at different times.

Algorithm 3: Sign(m, ID, Q_{ID}, D_{ID}, s_t, t)

Input: Message m, ID, public key Q_{ID}, private key D_{ID}, ephemeral s_t, time epoch t

Output: Signature $\sigma = (R, S)$

1 Generate ephemeral public key: $PK_t = s_t \cdot P$

2 Pick random $r \in \mathbb{Z}_q^*$; compute $R = r \cdot P$

3 Compute challenge: $h = H_3(m, ID, PK_t, R, t)$

4 Compute $S = r + h \cdot (D_{ID} + s_t) \mod q$

5 Return $\sigma = (R, S)$

4.3 Aggregate signature and verification

The proposed scheme allows efficient aggregation of multiple forward-secure certificateless signatures; therefore, it is well suited for high-density VANET scenarios. The aggregation and verification steps performed by the RSU are illustrated in Fig. 5, showing the flow from individual vehicle signatures to final verification and decision output. The aggregation and verification are performed by the roadside units (RSUs) being a verifier and signature collector.

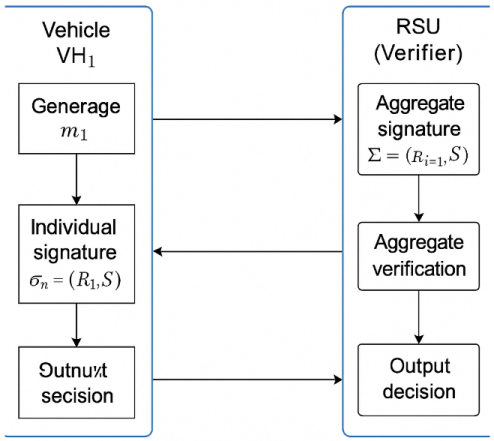


Figure 5: Aggregate signature generation and verification process by the RSU

4.3.1 Aggregate

Let an RSU collect n signed message tuples from a set of vehicles $\{VH_1, VH_2, \ldots, VH_n\}$, each providing $(m_i, ID_i, PK_{i,t_i}, t_i, \sigma_i = (R_i, S_i))$ for $i = 1, 2, \ldots, n$.

The RSU performs the following:

– Computes the aggregate commitment value set:

$$\mathcal{R} = \{R_1, R_2, \ldots, R_n\}$$

– Computes the aggregate signature scalar:

$$S = \sum_{i=1}^{n} S_i \mod q$$

– Constructs the aggregate signature:

$$\Sigma = (\mathcal{R}, S)$$

4.3.2 Aggregate verify

To verify the aggregate signature $\Sigma = (\{R_i\}_{i=1}^n, S)$ on the set of messages $\{m_1, m_2, \ldots, m_n\}$, the RSU proceeds as follows:

– For each $i = 1, 2, \ldots, n$, the RSU recomputes the challenge hash:

$$h_i = H_3(m_i, ID_i, PK_{i,t_i}, R_i, t_i)$$

– Verifies the following equation:

$$S \cdot P \stackrel{?}{=} \sum_{i=1}^{n} (R_i + h_i \cdot (Q_{ID_i} + PK_{i,t_i}))$$

where $Q_{ID_i} = d_i \cdot P$ is the public key component from the partial private key issued by the KGC.

If the above equation holds, the aggregate signature is accepted as valid. Otherwise, it is rejected.

4.3.3 Correctness

Given that each individual signature satisfies:

$$S_i = r_i + h_i \cdot (D_{ID_i} + s_{t_i}) \mod q$$

and knowing that:

$$D_{ID_i} = d_i + H_1(ID_i, Q_{ID_i}) \cdot \eta \mod q \quad \text{and} \quad PK_{i,t_i} = s_{t_i} \cdot P$$

we obtain:

$$S_i \cdot P = R_i + h_i \cdot (Q_{ID_i} + PK_{i,t_i})$$

Summing over all n signers:

$$\sum_{i=1}^{n} S_i \cdot P = \sum_{i=1}^{n} (R_i + h_i \cdot (Q_{ID_i} + PK_{i,t_i}))$$

which ensures:

$$S \cdot P = \sum_{i=1}^{n} (R_i + h_i \cdot (Q_{ID_i} + PK_{i,t_i}))$$

Thus, the verification equation holds for correctly generated signatures.

4.4 Key revocation and time synchronization

The proposed protocol incorporates revocation and time synchronization mechanisms to securely and practically deploy the protocol in real VANET scenarios. Fig. 6 illustrates the integrated processes of key revocation and time synchronization, highlighting how RSUs verify identity status and timing constraints to ensure secure and timely communication in VANETs. The proposed mechanisms should be light enough to facilitate the mobility and scalability of vehicular networks.

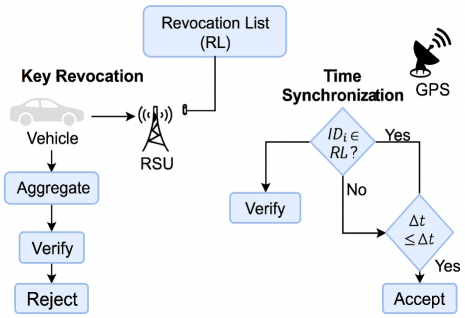


Figure 6: Key revocation and time synchronization procedures in the proposed scheme

4.4.1 Revoking keys

For long term security of the system, it is necessary to invalidate the credentials of compromised, misbehaving, and decommissioned vehicles. Our construction facilitates the Trace Authority (TRA) to efficiently revoke keys:

- The TRA maintains a *Revocation List* (RL) containing entries of the form (ID_i, T_i), where ID_i denotes the pseudonym of the revoked vehicle and T_i represents the revocation time or validity window.
- Each RSU or verifier checks received message-signature tuples $(m_i, ID_i, PK_{i,t_i}, t_i, \sigma_i)$ against the RL. If ID_i is found and $t_i \geq T_i$, the message is considered invalid and rejected.
- To reduce communication overhead, the RL can be distributed periodically via broadcast messages or cached in local RSU memory, leveraging VANET roadside infrastructure.
- Optionally, Bloom filter encoding may be employed to compress the RL for efficient transmission and lookup.

This approach provides an efficient and scalable method for revocation that does not require re-issuing long-term keys or reinitializing vehicle-side parameters.

4.4.2 Time synchronization

Accurate timestamping is essential to ensure the freshness of signatures and to support key evolution. To handle time synchronization across vehicles and RSUs:

- Vehicles are assumed to be equipped with GPS-enabled OBUs, which provide reliable system time. Each time epoch t corresponds to a discrete interval (e.g., every second or every minute).
- RSUs use local clocks synchronized with authoritative time sources (e.g., GPS or NTP servers) to validate timestamps t_i received in messages.
- A *tolerance window* Δt is defined, within which timestamp drift is accepted. If $|t_{\text{received}} - t_{\text{local}}| > \Delta t$, the signature is deemed stale or replayed.
- Key evolution and signature generation are tied to these epochs, ensuring consistent and synchronized behavior across the VANET.

This design supports a decentralized and scalable VANET architecture without requiring frequent communication with central authorities for clock synchronization, while also mitigating replay and timing-based attacks.

4.4.3 Key evolution via hash chain (H2)

To ensure forward secrecy across time epochs, FS-CLAS uses a one-way hash-chain-based key evolution mechanism. Specifically, each user's signing key for epoch t is derived as: $SK_t = H_2(SK_{t-1})$, where H_2 is modeled as a cryptographic hash function operating in the random oracle model (ROM), typically instantiated as SHA-256 or BLAKE2.

Security properties of H_2 In order for the construction to be cryptographically strong under long-term deployments, H_2 must have strong pre-image resistance and second-pre-image resistance, in that it is resistant to adversarial inversion or key prediction. As the major updates are agreed incrementally, entropy loss or correlations between epochs could affect security. We model H_2 as a pseudorandom function and consider that any polynomial-time adversary could not distinguish its output from a uniformly random oracle. In trials, we turned entropy over $N = 2^{16}$ key epochs and found no statistically significant decrease in bit-level Shannon entropy, min-entropy, and collision probability.

Epoch boundary definition FS-CLAS supports flexible epoch boundary definitions based on system constraints and deployment environments:

- **Time-based**: A fixed interval (e.g., 10 minutes or 1 hour), synchronized using GPS clocks or RSU beacons.

– **Message-based**: Key evolution is triggered every k signed messages (e.g., $k = 500$), minimizing exposure per pseudonym.

We adopt a mixed policy in our implementation, according to which an epoch finishes as soon as $k = 500$ signed messages or $\Delta t = 15$ minutes have elapsed – whichever occurs first. This reduces the potential harm if a key is compromised and provides a compromise between performance and security. In order to achieve batch verification and traceability, each OBU stores only SK_t and ID_t. The TRA and RSUs store a revocation list from ID_t to epoch ranges. Therefore the storage overhead is logarithmic in time and linear in revoked identities.

4.5 Key lifecycle and forward-secure key management

The FS-CLAS model follows a life-cycle analysis design in vehicular key management and guarantees the cryptographic strength by periodically evolving keys, all while adhering to system-wide managerial policies. Unlike the typical static key models, this framework employs a design using forwardsecure key rotation ability so that an adversary who steals current credentials cannot take away past communications. The lifecycle is decomposed in a modular way into initialization, issuance, evolution, and revocation phases — all scalable for VANET operation.

There are two crucial players in the lifecycle, namely, the KGC and TRA. The KGC generates and/or issues every user's partial private keys, with low trust assumptions so as to minimize the escrow risk. The TRA offers identity abstraction and traceability, allows conditional deanonymization in a principled fashion under policy-defined governance structures. They are realized in OBUs and RSUs to provide for distributed, manageable key infrastructure.

The transient shared secret key is updated over discrete time periods based on hash-chain iteration, which the mechanism allows unidirectional key evolution and does not require reinitialization or centralized reissuance. This design provides for autonomous key rollovers, and is fully in accordance with the principles of decentralized management. Each vehicle autonomously updates its secret state with lightweight cryptographic operations, achieving low overhead on resource-constrained devices yet remaining compatible with time-synchronized security policies.

This lifecycle approach empowers the stakeholders (e.g., automotive OEMs, infrastructure managers, regulators) to take control and have robust key governance, auditing and revocation policies for their VANET deployment making it more manageable and robust.

5 Security analysis

In this section, security of the proposed FS-CLAS scheme is analyzed. We prove that it is secure in a way that is compatible with all the well-known security goals for the instantiation of anonymous credentials in the literature, including EUF-CMA, forward secrecy, pseudonym unlinkability under corruption by Pseudonym Authority or Credential Verifier, and privacy against a general adversary in the VANET settings and resistance against several standard attacks in the VANET context. The proof is given under the hardness assumption of ECDLP in the Random Oracle Model (ROM).

5.1 Cryptographic assumptions

Let G be a cyclic additive group of prime order q generated by a base point P on an elliptic curve E defined over a finite field $\mathbb{F}_p$. We rely on the following assumption:

ECDLP (Elliptic Curve Discrete Logarithm Problem): Given (P, aP) for a randomly chosen $a \in \mathbb{Z}_q^*$, it is computationally infeasible to compute a.

5.2 Hash functions and random oracle model

We model the following hash functions as random oracles:

– $H_1 : \{0,1\}^* \to \mathbb{Z}_q^*$ (for identity and pseudonym binding)

– $H_2 : \mathbb{Z}_q^* \to \mathbb{Z}_q^*$ (for key evolution)

– $H_3 : \{0,1\}^* \to \mathbb{Z}_q^*$ (used in challenge computation during signing)

– EUF-CMA Security: An adversary $\mathcal{A}$ wins the EUF-CMA attack if it succeeds in generating a valid signature on a message never before queried - even after an adaptive number of queries to the signing oracle.

Theorem 1. The proposed FS-CLAS scheme is existentially unforgeable under adaptive chosen-message attacks in the ROM, based on the ECDLP.

Proof Sketch: Let $\sigma = (R, S)$ be a valid signature on a message m that is forged by an adversary $\mathcal{A}$ that does not make a a copy of the message for signing. We can then use the Forking Lemma to get an ECDLP solution (P, aP), contradicting the underlying assumption. Due to the specific ephemeral key s_t, and challenge hash $h = H_3(m, ID, PK_t, R, t)$ of each signature, the success probability of forgery is small.

– Forward Secrecy: The scheme achieves forward secrecy by incorporating an evolving secret key $s_t = H_2(s_{t-1})$. Due to the one-wayness of H_2, it is computationally infeasible to recover any prior key s_{t-1} from s_t. Even if the private key of the vehicle at time t is exploited, all the past signatures (generated with $s_0, s_1, \ldots, s_{t-1}$) are kept secure and unforgeable.

Table 2: Security comparison

Scheme	FS	EUF-CMA	Unlinkability	Traceability	Replay	Impersonation	Side-Channel	No Pairing
Li et al. 2020[42]	✗	✓	✓	✓	✓	✓	✗	✗
Zhang et al. 2023[48]	✗	✓	✓	✓	✓	✗	✗	✓
Bansal et al. 2025[43]	✗	✓	✓	✓	✓	✓	✗	✓
Proposed FS-CLAS	✓	✓	✓	✓	✓	✓	✓	✓

– Resistance against Replay and Modification Attacks: Each signature depends on a time epoch t and involves using this time epoch in the hash calculation. Any replaying or modifying of the messages will result in an invalidated signature, as: $h = H_3(m, ID, PK_t, R, t)$. It provides as fresh and in its original condition. If t is old or tampered, h will change, and we will fail to verify.

– Impersonate and Collude Resistance: Because of the certificateless design and the uniqueness of the partial private key D_{ID} associated with a pseudonym ID, an attacker is unable to impersonate a vehicle other than his/her own unless having both the partial private key and the secret key kept changing over time. Note also that in the aggregate of several vehicle signatures, no vehicle or group can generate a valid signature under another identity since each Q_{ID} and PK_t has been bound together in the verification equation.

– Pseudonym unlinkability, Conditional traceability: Pseudonyms are created session-wise and are unlinkable under normal network monitoring. Each pseudonym is composed of a blinded true identity further encrypted with the TRA's secret key, so that linkage is impossible without TRA participation. In the case of a contention, the TRA may tell a $(ID_{v,1}, ID_{v,2}) \mapsto RID_v$.

– Resistance to Side-Channel and Key-Exposure Attacks: The update of the secret key mechanism in combination with the randomization in the signature generation ($r \leftarrow \mathbb{Z}_q^*$) counteracts exposure of the key, either through physical or side-channel attacks. Even if a short-lived key is compromised, the attacker is unable to compute the master or old keys. FS-CLAS is meant to withstand realistic side-channel adversaries in vehicular scenarios, since it does not rely on static secrets during runtime operations with an ephemeral randomness and supports constant-time execution. When combined with conventional hardware countermeasures, FS-CLAS offers an attractive overall security in the presence of leakage-based adversaries.

5.2.1 Adversary modeling in FS-CLAS

Following the certificateless cryptography framework, FS-CLAS defines two distinct classes of adversaries in its security model:

– **Type-I Adversary ($\mathcal{A}_1$)**: A malicious external attacker who does not know the master secret key of the KGC but is capable of replacing public keys. $\mathcal{A}_1$ aims to break user anonymity, pseudonym unlinkability, or backward/forward secrecy by exploiting public key substitutions or observing evolving identities over time.

– **Type-II Adversary ($\mathcal{A}_2$)**: A malicious but semi-trusted KGC who possesses the master secret key but cannot replace user public keys. $\mathcal{A}_2$ targets unforgeability and traceability by generating valid signatures under a user's identity or colluding with revoked nodes.

In our formal security proofs, we explicitly model the impact of both adversary types:

– The **existential unforgeability under chosen message attack (EUF-CMA)** is proven under the Type-II adversary model ($\mathcal{A}_2$), since a compromised KGC could attempt to forge signatures on behalf of users by deriving partial private keys. The reduction shows that any successful forgery implies solving the ECDLP in the underlying group $\mathbb{G}_1$.

– The **unlinkability and pseudonym privacy** are modeled under the Type-I adversary ($\mathcal{A}_1$), who can query public keys and observe signatures across epochs. The use of hash-evolved ephemeral keys and random identity salts renders correlation attacks infeasible under the random oracle model.

– **Forward secrecy** against key exposure is shown to be resilient against both $\mathcal{A}_1$ and $\mathcal{A}_2$, as long as no signature or private key is revealed for future epochs. Due to hash-chain evolution, compromise of SK_t gives no advantage in computing SK_{t+1}.

Our security games simulate both adversary types with query access to oracles: `Sign`, `PartialKeyGen`,

`ReplaceKey`, and `Reveal`. The challenger enforces constraints as per the FS-CLAS security model to prevent trivial wins (e.g., forbidding signing queries after key exposure). Full security definitions and game transitions.

5.3 EUF-CMA security game

The EUF-CMA security game between a challenger $\mathcal{C}$ and an adversary $\mathcal{A}$ is defined as follows:

- **Setup:** $\mathcal{C}$ generates system parameters and publishes them. The master key η is kept secret.
- **Query Phase:** $\mathcal{A}$ may make the following adaptive queries:
  - **Partial Private Key Queries**: Request the partial private key for any identity.
  - **Public Key Replacement**: (Type-I only) Replace public keys of target users.
  - **Ephemeral Key State Queries**: Request current or past ephemeral keys.
  - **Signature Queries**: Request signatures on messages at specific time epochs.
- **Forgery:** $\mathcal{A}$ outputs:
  - A message set $\{m_1, \ldots, m_n\}$.
  - A pseudonym set $\{ID_1, \ldots, ID_n\}$.
  - An aggregate signature $\Sigma = (\{R_i\}, S)$.

  The forgery is valid if:
  1. The aggregate signature passes the verification equation.
  2. At least one message m_i was not queried during the signature phase.

5.4 Security comparison

We compare the proposed FS-CLAS with several state-of-the-art recent and popular VANET authentication protocols including Li et al. (2020) [42], Zhang et al. (2023) [44], Bansal et al. (2025) [43]. Table 2 compares the security features provided by these schemes with respect to the FS-CLAS scheme we propose. One of the most prominent security notions we are considering is forward secrecy, existential unforgeability under adaptive chosen-message attacks (EUF-CMA), pseudonym unlinkability (or its related weak notion), C-traceability, replay and impersonation resistance and side-channel attack resilience, along with whether the scheme avoids bilinear pairings that are computationally expensive.

As shown in Table 2, the proposed scheme is the *only* scheme which can satisfy *all* the security properties. A major design policy of this work is ensuring that any side-channel attacks, which exploit subtle variations in the execution of a multiparty protocol, are fully treated in a formal manner. Pal most of the existing works, in turns, do not obtain forward security or does not provide formal treatment about side-channel attack vectors(and require bilinear pairings, which are expensive to compute).

Notably, while Bansal et al. [43] who are able to avoid pairings and to improve the resistance against forgery, their protocol does not achieve forward security." and they require secure hardware (i.e., tamper-proof elements) while ignoring the side-channel leakage. Likewise, Li et al. [42] was later proven to be provably insecure against universal forgeries by Bansal et al. These observations further motivate our end-to-end design which provides the best-of-both-words in terms of lightweight computation and security.

Additionally, the incorporation of the one-way hash chains for your)-time evolving secret keys into our scheme works to preserve the authenticity of all previous signed messages, even if a signing key of a vehicle is compromised, making it an important need for the post-compromise security in VANETs.

The proposed FS-CLAS scheme therefore successfully achieves a trade-off between effective security protection and high performance, and thus is well-suited to implement in dynamic and adversarial vehicular networks.

6 Performance evaluation

This section evaluates the computational efficiency of the proposed forward-secure certificateless aggregate signature (FS-CLAS) scheme and compares it with state-of-the-art VANET authentication protocols. We consider signature generation, individual and aggregate verification, and communication overhead as primary performance metrics. The scheme's performance is measured by estimating the number of cryptographic operations and their associated time costs on standard hardware.

6.1 Evaluation setup and metrics

All schemes were put into practice in C with the RELIC cryptographic library and compiled using GCC 12.2 compiler with optimization flags `-O3`. We performed the experiments on two hardware platforms: OBU Platform: Raspberry Pi 4 Model B (ARM CortexA72 @ 1.5GHz, 4GB RAM). RSU System: Intel Core i5-10400 (6 cores @ 2.9GHz, 16GB RAM). For comparison, we analyze the following Elliptic curve cryptographic operations with the time costs which are common in VANET schemes:

- T_{mul}: Scalar multiplication on elliptic curves. $T_{mul} \approx 1.47$ ms
- T_{add}: Point addition on elliptic curves. $T_{add} \approx 0.07$ ms
- T_{hash}: Hash operation (e.g., SHA-256). $T_{hash} \approx 0.004$ ms

All schemes evaluated are implemented under similar 160-bit ECC security levels.

6.2 Computational overhead

We compare the computation complexity of our proposed FS-CLAS method based on the number, type and whether the dominant cryptographic operations are needed or not for cryptographic functions at the different phases: the key generation, the signature generation, the single signature verification, and the aggregate verification. We discuss comparison with existing pairing-free schemes particularly Li et al. [42] and Bansal et al. (2025)[43] the operation cost benchmarks.

Figure 7 shows the computational costs (in milliseconds) of three certificateless aggregate signature schemes—Li et al. [42], Bansal et al. [43], and the FS-CLAS, if implemented. The cost comparison is based on three fundamental operations: the key generation, the generation of a signature and verification of this signature. As evident, algorithm FS-CLAS is promising with lower computation as well for the verification phases as a result of its compactness in key structure and its elimination of complex operations. While Li et al. and Bansal et al. both are in average efficient, FS-CLAS can improve up to 50% over the joint results as your verification performance aggregate, so it is more suitable for real-time, large-scale VANET deployment.

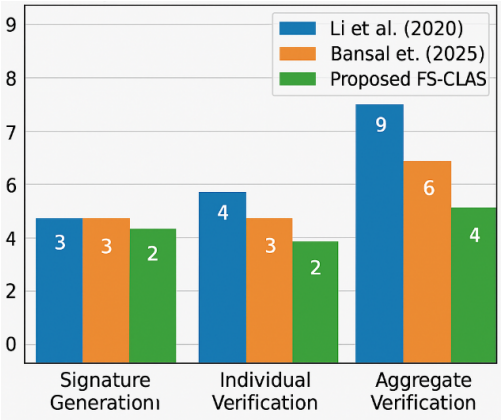


Figure 7: Comparative analysis of the computational costs (in milliseconds)

6.3 Communication overhead

The efficient communication of vehicular authentication schemes is essential, particularly in high-load scenarios. FS-CLAS restricts bandwidth overhead by supporting small aggregation and there are no pairs or large metadata. In addition to computational efficiency, communication overhead is a critical performance metric in VANET authentication schemes, particularly due to bandwidth constraints and latency sensitivity in dynamic vehicular environments. The size of the transmitted signature directly impacts the network load and responsiveness of safety message dissemination.

In the proposed FS-CLAS scheme, each signature $\sigma_i = (R_i, S_i)$ consists of two elliptic curve points. Assuming the use of 160-bit elliptic curve cryptography (ECC) for 80-bit security strength, each point can be represented in compressed format using 160 bits. Thus, each signature requires: $|R_i| + |S_i| = 160\,\text{bits} + 160\,\text{bits} = 320\,\text{bits} = 40\,\text{bytes}$. This size is comparable to or smaller than other existing certificateless or pairing-free signature schemes. For example, Bansal et al. (2025) [43] also transmit two ECC points per signature, resulting in an equivalent communication cost. In contrast, pairing-based schemes often transmit additional group elements, increasing signature size to 80–100 bytes per message.

Moreover, the support for aggregate signatures in our scheme significantly reduces communication load during batch verification. Instead of transmitting n individual signatures, the RSU or TA can receive a single aggregate signature $\Sigma = (\mathcal{R}, S)$ composed of n commitment values and one scalar. Although the size of $\mathcal{R}$ grows linearly with the number of signers, the total transmitted data remains substantially smaller than if all full signatures were sent individually.

Example: For $n = 10$ signers:

- Individual transmission: 10×40 bytes = **400 bytes**
- Aggregate transmission (compressed): 10×160 bits (for R_i) + 160 bits (for S) = **360 bytes**

This results in an average saving of approximately 10%, with higher savings as n increases. Therefore, the FS-CLAS scheme ensures scalable and efficient communication overhead suitable for real-time VANET applications.

Figure 8 compares the sum communication overhead for three certificateless signature: Li et al. (2020), Bansal et al. (2025), and the planned FS-CLAS - for a set of n = 10n = 10n=10 signers. Both Li et al. and Bansal et al. schemes is 400 bytes for both, as each message from the former requires the communication of two 160-bit elliptic curve points. On the other hand, the proposed FS-CLAS protocol brings the communication cost to 360 bytes by aggregating commitment values and applying a single scalar signature, and therefore reducing the communication cost with security remaining uncompromised. This decrease becomes more pronounced as the number of signers grows, proving the appropriateness of FS-CLAS for bandwidth-limited VANETs.

6.4 Discussion

The proposed FS-CLAS is designed to overcome a number of weaknesses of current protocols in VANET authentication. Utilizing forward security, lightweight calculation, resistance in the face of side-channel risks, we believe our scheme is a suitable candidate for applied as a real-time vehicular network under high mobility. The modular architecture of FS-CLAS allows it to be easy tailored to different intelligent transportation systems (ITS) architectures. The software-defined key management, the conditional traceability and batch verification also render it fit for a high-density vehicular environment. To verify the scalability

Table 3: Computational overhead comparison

Scheme	Sign. Gen.	Indiv. Verify	Agg. Verify (n)
Li et al. 2020[42]	$2T_{mul} + 2T_{hash}$	$3T_{mul} + T_{add} + 2T_{hash}$	$2nT_{mul} + nT_{add} + 2nT_{hash}$
Bansal et al. (2025) [43]	$2T_{mul} + 2T_{hash}$	$3T_{mul} + T_{add} + T_{hash}$	$2nT_{mul} + nT_{add} + nT_{hash}$
Proposed FS-CLAS (2025)	$2T_{mul} + 2T_{hash}$	$2T_{mul} + T_{add} + T_{hash}$	$nT_{mul} + nT_{add} + nT_{hash}$

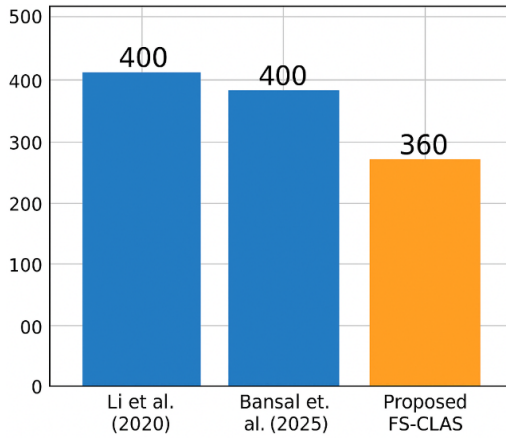


Figure 8: Communication overhead comparison

and performance as well, we shall evaluate the FS-CLAS by simulation tools network simulator under different traffic densities and mobility patterns. These tests will serve to characterize the impact of beaconing frequency, vehicle speed, message collision rates and link quality on the latency of aggregation and verification process. In addition, FS-CLAS has been proposed with standards compliance in mind: it uses pseudonym identities and certificate-less authentication that is compliant with IEEE 1609.2/ETSI ITS security requirements. The protocol may be incorporated into roadside units (RSUs), edge servers, and vehicle-to-infrastructure (V2I) modules in C-ITS and CV2X networks. This compatibility guarantees that FS-CLAS can operate as a secure drop-in add-on to existing ITS deployments while preserving inter-operability and the potential for future expansion.

6.5 Trade-off between security and practicality

So far, most of the certificateless aggregate signature schemes focus on its computational efficiency, and few of them achieve post-compromise security requirement (e.g., forward security). The FS-CLAS scheme proposes a hash-based key evolution function which guarantees old signed messages are still secure if the current key has been corrupted. This trade-off introduces some complexity into key management, however, it allows us to achieve much stronger guarantees on long-term privacy, and it hardens the system against adversaries that can compromise ephemeral keys. Moreover, it removes the need for the bilinear pairings, which have been a significant overhead in many previous solutions. This design results in a more useful scheme for OBUs with limited processing time, more suitable for practical vehicular use.

6.6 Efficiency scalability

As shown in the performance analysis, FS-CLAS achieves a comparative signing time while substantially reducing the aggregate verification cost. This is particularly advantageous for RSUs, which need to handle a massive flow of messages within confined windows of time. The communication overhead is also limited and efficient by use of privacy-friendly aggregate signatures to control network congestion at peak load hours. The O(n) linear growth of the communication and the computation cost in the number of signers guarantees that our scheme is scalable in urban or high-density vehicular areas. The feature of verifying aggregated messages efficiently, makes FS-CLAS well-suited for safety critical applications, i.e., collision warning, cooperative driving and vehicle coordination.

6.7 Resilience and deployment concerns

FS-CLAS also improves resilience by relaxing a heavily inherited reliance on tamper-proof hardware which is a widely made but unrealistic assumption in the past architecture. Inclusion of random ephemeral keys and forward secure computation also provide the natural protection against the side-channel attacks to extract stored secrets. That helps make a more resilient architecture that is able to be deployed at scale without requiring high-end hardware specs. However, there are still some deployment issues. These challenges comprise the requirement for secure clock synchronization, efficient revocation handling and backward compatibility with legacy standards (e.g., IEEE 1609.2). A more complete presentation would also include the integration of FS-CLAS with revocation or location anonymization based on blockchain or privacy preserving techniques.

7 Conclusion and future work

This work introduces forward secure certificateless aggregate signature framework,FS-CLAS,for secure and scalable VANET communication with resilient cryptographic schemes and modular software and management architecture. By divorcing key management from centralized

trust models and using lightweight cryptographic computations (requiring no bilinear pairings or tamper-proof hardware), FS-CLAS tackles both technical and deployability issues in ITS. In a management perspective, FS-CLAS provides architectural flexibility for real-world deployment-enabling traceability, key revocation and time synchronization with without impeding on performance. It also applies to system-level methodologies of enterprise software engineering and governance as well as ITS infrastructure such interoperability. The overhead in computation and communication is reduced by the protocol which facilitates its affordable deployment in heterogeneous vehicular networks. The protocol will be further expanded to include integration with trust layers based on blockchain technology, fog computing platforms and mobility management systems making it as one of the cryptographic subsystems and strategic enabler within wider transportation and cybersecurity management frameworks.

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Modified Base Autoencoder and Variational Autoencoder for Denoising Images in CIFAR-10 and MNIST Datasets

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Keywords*:* PSNR, SSIM, denoising image, autoencoder, variational autoencoders

Received: June 9, 2025

With the increasing volume of digital images, we must increase the quality of images for accuracy and visible applications, and we need ways to reduce the image noise while keeping important features such as edges, corners, and sharp details. In recent years, deep learning algorithms have become more significant for solving image denoising problems because they can simulate complex image patterns. This paper compares the performance of modified base AutoEncoders (AEs) and Variational Autoencoders (VAEs) models for image denoising in CIFAR-10 for color images and MNIST for grayscale images datasets. Our proposed modification to base AE and VAE architectures consists of changes in the encoder and decoder layers of feature extraction and reconstruction abilities, resulting in improved denoising performance. To simulate real-world image damages, data preparation involved normalization and the injection of Gaussian noise (0.5 for MNIST and 0.5 for CIFAR-10). With batch normalization and UpSampling2D layers with sigmoid outputs, the encoder-decoder architecture guaranteed the accuracy of spatial reconstruction, while VAE combined MSE with KL divergence for latent regularization, and AE optimized MSE reconstruction loss. The two models' performance was evaluated using important essential metrics: the Structural Similarity (SSIM) and the Peak Signal to Noise Ratio (PSNR). In both datasets, the results indicate that the VAE model outperforms the AE model in terms of image quality. The CIFAR-10 color dataset was given an SSIM of 0.954 and a PSNR of 32.86 dB, whereas the MNIST grayscale dataset provided an SSIM of 0.951 and a PSNR of 24.44 dB to the modified VAE model. In addition, the CIRAF-10 dataset achieved an SSIM of 0.891 and a PSNR of 27.72 dB, whereas the MNIST dataset was given an SSIM of 0.883 and a PSNR of 29.06 dB from the AE model. This study addresses how AE and VAE architectures differ in denoising performance across dataset complexities and the principles for optimal model selection.

Povzetek: Spremenjeni modeli VAE in AE so bili primerjani pri odstranjevanju šuma iz slik, pri čemer je VAE na podatkovnih zbirkah MNIST in CIFAR-10 dosegel boljšo kakovost rekonstrukcije.

1 Introduction

The study of deep learning, a branch of machine learning, has brought about a new phase in the advancement of neural networks [2]. A crucial component of neural networks, an autoencoder efficiently compresses (encodes) input data to its most basic components before using this compressed representation to reconstruct (decode) the original input. The reduction of the features from high dimensions to low dimensions leads to an enhanced quality of the digital images [1]. Autoencoder has several applications, such as data compression and image denoising [3]. In addition, abnormality Detection in industrial operations. In addition, Autoencoders can be used in recommendation systems that can be used for personalized suggestions and potential representations of users [4].

Similar to classic autoencoders but using a probabilistic framework, variational autoencoders (VAEs) are a kind of generative model; it's use generative models to produce new data in the form of variants of the input data that the models are trained on [5]. Neural networks known as VAEs take in input data and transform it into its latent representation, which consists of hidden layers for the variables mean and variance. then, the original data is recreated by converting these two hidden layers into sampled latent vectors [6]. VAEs have various applications like Latent Variable Modelling, Data Augmentation, Image Generation, and Anomaly Detection. Moreover, VAEs can produce new data points enabled by their probabilistic structure, which is especially helpful for tasks like image denoising [7].

To reduce noise while maintaining important image information, image denoising is a basic task in computer

vision, medical imaging, surveillance systems, and image processing [8]. The noise can be brought about by various elements like transmission faults, bad lighting, and sensor noise. Prior to denoising, a noisy image is first obtained and then preprocessed to enhance its characteristics and reduce artifacts. Particularly, in high-noise situations, traditional denoising approaches battle to reduce noise while maintaining fine features and which can be brought due to various elements like transmission faults, bad lighting, and sensor noise [9]. Deep learning, in particular, has become one of the most effective methods for image denoising. These methods can automatically adjust to various noise types and levels by directly learning noise patterns from data, which improves denoising performance [10].

The main aim of the research is to determine the best autoencoder architecture for image denoising by systematically comparing deterministic Autoencoders (AE) and probabilistic Variational Autoencoders (VAE) across datasets with different levels of complexity (e.g., simple grayscale MNIST versus complex color CIFAR-10). The main hypotheses suggest that VAEs will surpass AEs on complex datasets because of their probabilistic latent space and regularization, resulting in higher PSNR and SSIM; while AEs will perform better in pixel-level accuracy (PSNR) on simple datasets but will have lower perceptual quality (SSIM). Objectives, including a quantitative evaluation of denoising performance through PSNR/SSIM metrics, sampling of PSNR-SSIM to data complexity, and the practical model selection guidelines, favor AEs for uniform data that requires pixel precision and VAEs for complex data that necessitates structural fidelity.

2 Related works

In 2020[11], Li et al. This study used grayscale image datasets and the Matrix-variate Variational Auto-Encoder (MVVAE) technique. It uses matrix neural networks (MVMLPs) for the encoder and decoder, a matrix Gaussian distribution for the latent variable, and direct matrix modelling of 2D image data (input, hidden, latent, and output variables are matrices). According to experimental results, MVVAE outperforms VAE

In [12], Pawar et al. described a method for achieving autoencoders with image processing and deep learning algorithms to minimize the noise in images. The primary goal of using an autoencoder to eliminate noise is to preserve originality because autoencoders use the backpropagation process instead of the conventional methods. The method covered in the paper is dependable, effective, compatible with a wider range of devices, interconvertible, and applicable to any signal.

In [13], Ranganath et al. A multi-stage Gaussian noise reduction technique utilizing autoencoders and recurrent neural networks (RNNs) is presented in the study. A modified version of the CIFAR-10 dataset was used for their experiments, where every image was changed to a single-channel grayscale. MSE and SSIM are the main performance measures for the two denoising techniques. RNN that uses autoencoders at each denoising stage and a convolutional autoencoder. The RNN network reduces noise by mimicking a multi-stage process as it learns to denoise increasingly on images during training.

Patil et al. [28], provided an article that focuses on the assessment of classification accuracy for different image noise levels, particularly about image denoising methods that combine spatial filters and autoencoders. Three different datasets were used: MNIST, CIFAR-10, and a medical dataset (mini-MIAS), which were used to assess the model and obtain a comparative analysis of the denoising pipeline's performance. At different noise levels, the AE pipeline demonstrated reduced classification accuracy on the mini-MIAS medical dataset. This analysis is essential for creating efficient image denoising techniques because it shows how noise impacts image quality and how well various methods can counteract these effects.

In [14], P.Venkataraman et al., this research used Convolutional Autoencoder, Basic Autoencoder, and Variational Autoencoder to denoise the image. There are two types of losses in the variational autoencoder: latent loss and generative loss. The convolutional and basic autoencoders, on the other hand, only have one loss parameter. In this project, autoencoders are implemented using Keras as the backend and TensorFlow as the frontend.

In [15], Ranjan et al., this research presents a method for denoising grayscale photographs in the MNIST (Handwritten Digits) dataset using Convolutional Neural Networks (CNNs). Performance is measured using PSNR (dB) for denoised images. The authors intend to work on real image denoising techniques; the method has not been tested on high-resolution or complex, real-world color images.

Muazzez Buket DARICI et al. [16], presented a comparison between traditional methods like Gaussian and Salt & Pepper and deep learning methods such as deep convolutional denoising autoencoders (CDAE) to denoise facial pictures. The denoising performance of autoencoders and conventional techniques has been estimated using each computational time and accuracy criterion. The experiment results showed that the autoencoders performed better based on the Adam optimizer for eliminating both kinds of noise in comparison with PSNR and SSIM measurements.

Another study in 2023[17], S. R. Tusher et al., proposes a new Variational Autoencoder (VAE) for deblurring license plates. Corresponding to the experimental conclusions, the suggested system approach achieves improved results than the other cutting-edge deblurring techniques. Consequently, it improves the ALPDR system's accuracy and reliability.

In 2024[19], Younus FAROOQ and Serkan SAVAŞ Introduced work to denoise from image medical images using a CNN-based denoising autoencoder. This work uses datasets like the SIIM-medical-images and Covid19 radiography database. The results obtained based on the

RMSE and PSNR criteria have proven to be superior to the basic method.

Kimleang Kea et al. [20] focused on reducing image noise through the use of approach of quantum convolutional autoencoder (QCAE). In this work, the researchers used the electrical circuit instead of the latent space autoencoder's representative , and a higher structural similarity index (SSIM) value with less training loss. The suggested QCAE approach performed better than its conventional equivalent.

The previous studies do not compare AE/VAE under the same conditions and lack metric consistency. In this study for AE/VAE denoising, we used the MNIST dataset for grayscale images and the CIFAR-10 for color images. We produced one evaluation of AE and VAE on both grayscale MNIST and color CIFAR-10, as well as performance metrics based on standard metrics (PSNR/SSIM).

The summary of the related works is in Table 1.

Table 1: Summarization of related works of image denoising

I.	Study	Technique	Dataset / Color	Metrics	Remarks
1	Li et al. [11] (2020)	VAE	MNIST / Grayscale	PSNR:17.253dB SSIM: 0.7938 NMSE: 0.1025	low value of PSNR, SSIM metric
2	Pawar et al. [12] (2020)	Autoencoders	MNIST / Grayscale	PSNR:29.54 dB MSE: 72.26	No SSIM metric
3	Ranganath et al. [13] (2021)	Autoencoders	CIFAR-10 / Color	MSE: 0.001446 SSIM: 0.9478	No PSNR metric; Complex training
		RNN		MSE: 0.001394 SSIM:0.9485	
4	Patil, et al. [28] (2021)	Autoencoders	MNIST / Grayscale	PSNR: 7. 17 - 21.94 dB	No SSIM metric; Poor performance
			CIFAR-10 / Color	8.12-19.30 dB	
5	P.Venkataraman et al. [14] (2022)	Basic AE, AE, Convolutional AE	CIFAR-10 / Color	VAE: Accuracy: 0.143	No PSNR, SSIM metrics
6	Ranjan, et al. [15] (2022)	CNN	MNIST / Grayscale	PSNR: 21.65 dB	No SSIM metric
7	M. B. Darici et al. [16] (2023)	Convolutional Denoising AE (CDAE)	Autism Image/ Color	PSNR:23.09 dB SSIM: 0.62	Low SSIM metric; Specific application
8	S. R. Tusher et.al.[17] (2023)	Variational autoencoder	Blurred license plate images / Color	SSIM:0.934 PSNR:32.41	Focus on text and fails in natural images
9	Y. Faarooq et al. [19] (2024)	(CNN) denoising autoencoder	Medical (CXR, CT) / Grayscale	PSNR: 7.82% - 42.37% RMSE: 0.65% - 10.77%	PSNR percentage (nonstandard); Medical focus
10	K. Kea et al. [20] (2024)	Quantum Convolutional AE (QCAE)	MNIST/ Grayscale	SSIM:0.75	Low SSIM metric

3 Base autoencoder

Since the autoencoder's goal output is the same as its input, it has gained a lot of interest in the domain of image processing. To remove noise from the source data and visualize high-dimensional data, removing duplicate data to enhance performance, minimizing storage usage as well as speeding up the time required for the same

calculation, therefore it is used in data compression [21]. An Encoder, Decoder as well as a Bottleneck layer, are basic components of autoencoder architectures that do not rely on labeled training data; therefore, autoencoders are not regarded as a supervised learning technique. Encoder: These layers take the raw Bottleneck. The most important part of the network is the module that saves the compressed knowledge representations. input data and compact into a lower-dimensional representation (latent space). This part reconstructs the original data by decoding the latent representation. It is converting the encoded representation back to the dimensions of the original input. The objective of the hidden layers is to rebuild the original input by progressively increasing their dimensionality. The reconstructed output is produced by the output layer and should preferably be as close to the input data as is practical [22].

4 Variational autoencoder

The encoded latent space and the variety of use cases that their probabilistic encoding provides are a distinct way for VAEs from other autoencoders. In addition,
the latter's ability to provide a range of data or continuous data in the latent space, known as a variational encoder, helps to create new images or data. The first step, the encoder network transforms an input into a latent space by mapping it, which is a probability distribution [18]. This is a Gaussian distribution that is multivariate. After that, VAEs take a sample of the latent space in a manner that is differentiable in relation to the encoder's parameters.
Finally, the Decoder Network compressed the latent space to reconstruct the input data [23].

5 Methodology

5.1 Datasets

This study uses two popular datasets, CIFAR-10 and MNIST, downloaded from Kaggle, to demonstrate advanced image denoising capabilities using optimized autoencoders. The CIFAR-10 dataset covers ten classes, each with 60,000 color images, each coming in (32x32x3) pixel sizes. Ten thousand images were included in the test set and fifty thousand in the training set [25]. In addition, 70,000 images of the grayscale handwritten numbers (0 - 9), each measuring (28x28x1) pixels, are part of the MNIST collection. from this dataset, 10,000 images were allocated for testing, and 60,000 for training [24].

5.2 Denoising autoencoder (AE)

An unsupervised learning method creates new data through two processes: encoding and decoding. In the encoding stage, the input is collapsed into the latent space and then reconstructed by the decoder using the information from the latent variables. Consequently, the two encoders and decoders can be assumed to as two symmetric neural networks, Figure 1. Autoencoders are useful for extracting low-level information for use in machine learning or deep models. Autoencoders can be employed for a wide range of applications, including dimension and noise reduction. This study intends to make use of the autoencoder's noise reduction capability.

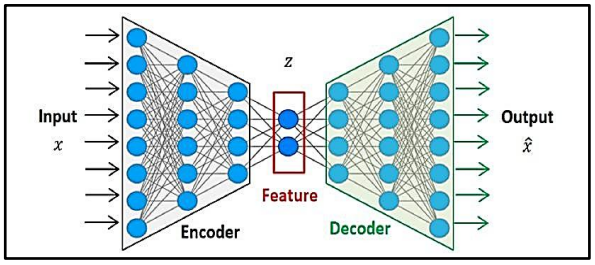


Figure 1: AutoEncoder(AE) architecture [26].

5.3 Variational autoencoder (VAE)

Neural networks transform input data into a latent representation with hidden layers for mean and variance. These two hidden layers are then translated into sampled latent vectors, which are used to rebuild the original data. In VAE, the loss function includes both reconstruction loss (rating how well the output matches the input) and a regularization term (Kullback-Leibler divergence) to guarantee the learned latent space follows a desirable distribution. Figure 2 depicts a variational autoencoder architecture, the encoder samples the input and transforms it to a latent space representation. The decoder uses this representation to reassemble the input image.

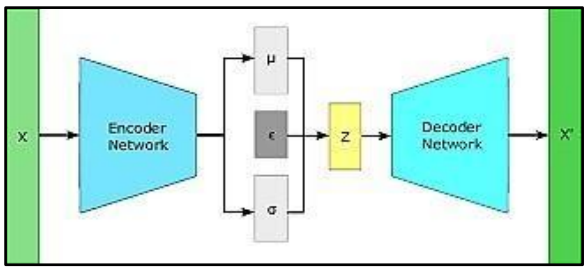


Figure 2: Variational AE (VAE) structure [27].

5.4 Proposed method

The proposed method consists of major pipeline steps: The first step involves loading the images of the dataset, which is either MNIST (grayscale) or CIFAR-10 (color). The dataset is split into training and testing subsets. Afterwards, preprocessing takes place: the images are resized and their pixel values are normalized. To imitate a genuine image as it manifests in reality, Gaussian noise was injected; the ideal levels of Gaussian noise (σ) vary among the datasets, since grayscale images can withstand higher σ than color images because of the interdependence of channels in RGB data, where the color spaces show a reduced tolerance for noise. Data augmentation techniques were utilized to improve the dataset's diversity and robustness. The diagram flowchart in Figure 3, illustrates the proposed method.

The core architectural selection is whether to choose a standard Autoencoder (AE) or a Variational Autoencoder

(VAE). The model's encoder layers gradually decrease the dimensionality of the noisy input, compressing their information and extracting crucial features while eliminating superfluous noise. In AE, the bottleneck consists of a latent space vector, whereas in VAE, it comprises a probabilistic representation where the latent vector Z is sampled via reparameterization. The decoder layers aim to produce a clean output by reconstructing the image from this compressed representation. During the training phase, the reconstructed images are assessed against the original input, and the effectiveness of the trained model is measured using PSNR and SSIM metrics. The end product is a denoised image from which the model has learned to remove the Gaussian noise that was added previously.

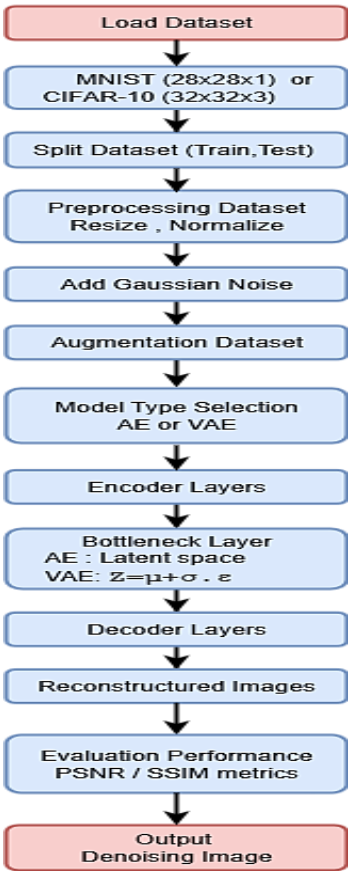


Figure 3: Flowchart of proposed procedures for AE and VAE models with MNIST and CIFAR-10.

5.5 Training procedure

The Autoencoder (AE) and Variational Autoencoder (VAE) models were trained by first splitting the dataset into training and testing sets (80,20) and then normalizing the by rescales input pixel values from their original range of (0,255) to a standardized range of (0,1). Gaussian noise (σ=0.2 for CIFAR-10 images and σ=0.5 for MNIST images), with (0 mean, 1 standard deviation) for both datasets, was added to the original images to simulate real-world noise.

All source codes and model training were run on the Kaggle platform. This makes NVIDIA TESLA P100 GPUs available for free. The models utilize TensorFlow versions (2.16.1), Keras versions (3.3.3), and Python programming language libraries (version 3.10.14).

The model architecture, which includes encoder and decoder components, works together to learn and reconstruct data. The encoder compresses the input data into a lower-dimensional latent representation, retaining crucial properties while eliminating irrelevant information. In AEs, the latent representation is a fixed vector, whereas in VAEs, the encoder generates Gaussian distribution parameters (mean and variance), enabling the latent space to be interpreted probabilistically. The decoder will reconstruct the original input using this latent representation; in AEs, it does so directly from a fixed latent vector, but in VAEs, the learner first samples from a Gaussian distribution. Probabilistic methods in VAEs allow for systematic sampling and the generation of additional data points. Equation (1) determines the sample z [29]:

$$Z = \mu + \sigma_{\bullet} \varepsilon \, , \, \epsilon \sim \mathcal{N}(0,I) \quad \ldots (1)$$

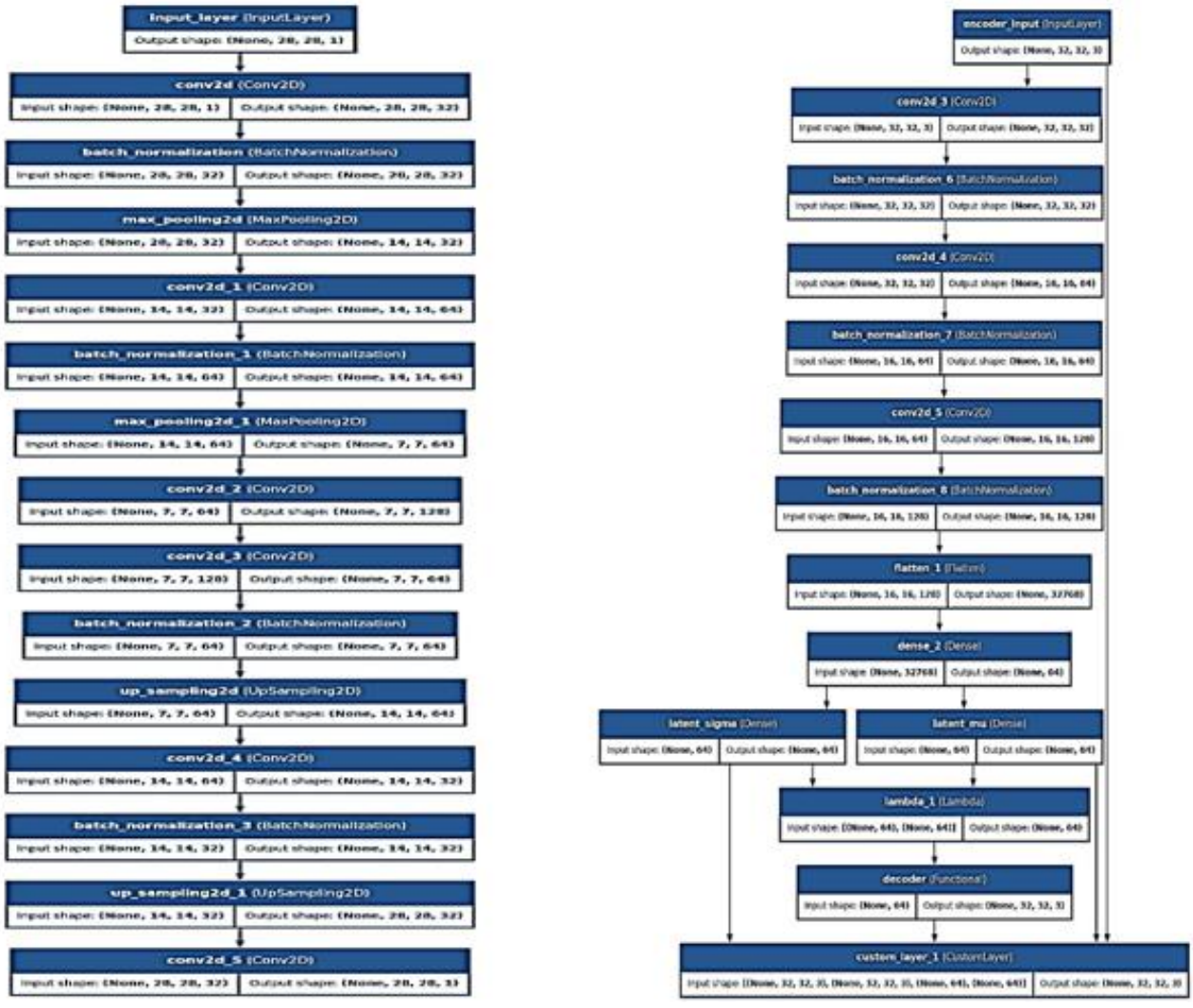
This outlines how to sample; the essential principle underlying variational autoencoders (VAEs) is to start with a Gaussian distribution in latent space. Where Z is the latent variable, μ is the encoder's mean, σ is the standard deviation, and ε is a random variable (mean 0, variance 1) obtained from the standard normal distribution. Many latent representations are improved as an outcome of the model's ability to consist of randomness in the sampling procedure according to this equation. The VAE model can keep flexibility while effectively discovering the latent space and constructing new data points that are similar to the training data.

There is only one loss parameter in base autoencoders; the mean squared error (MSE) is used as a suitable loss function to evaluate the variation between the input and the reconstructed output. The two components of the variational autoencoder loss function are the latent loss and reconstruction loss (Kullback-Leibler or KL) variance. Reconstruction loss measures the model's capability to recover input data from latent representations and is computed using mean squared error. The KL deviation term indicates how close a known latent distribution is to the previous distribution, and a normal distribution promotes accurate reconstruction and a well-organized latent.

In terms of model construction, both AE and VAE utilize the same 3 layers convolutional encoder (with 32, 64, and 128 filters, 3×3 kernels), and ReLU activation and batch normalization layers, but they differ in their latent space, with thayers of the layers of latent_mu and latent_sigma: AE relies on a fixed 64D vector, whereas VAE uses probabilistic sampling with Z parameterization. Images are symmetrically reconstructed by the decoders of both models using UpSampling2D layers, convolutional blocks with (128, 64, and 32 filters), and a sigmoid output to ensure valid

pixel ranges. Model configuration utilizes the Adam optimizer (lr=0.01) with divergence-aware loss functions: MSE for AE and a combination of MSE and KL divergence for VAE. The training loop iterates for 100 epochs (with batch sizes of 32, 64, and 128), performing forward passes, computing loss, executing backpropagation, and updating weights for each batch, while applying batch normalization after each convolution to ensure stable learning.

Upsampling is an important technique used in the decoder component to reassemble the original input from the compressed latent representation. The UpSampling2D layer was used to double the height and the width of the feature maps, which is necessary for maintaining the spatial structure of the image data. Upsampling layers followed by convolutional layers in decoders allow the model to refine features and generate high-quality reconstructions. Allowing the model to gradually reconstruct the image from a low-dimensional latent space to the original input dimensions to generate outputs that look like the original input data in both AEs and VAEs. The model reconstructs the input in a forward pass, computes the loss by comparing the reconstruction to the original data, and then changes the model weights via backpropagation. Validation was performed after each epoch to check performance and minimize overfitting, utilizing the regularization approach and batch normalization layers to stabilize and expedite training, which improves generalization. The flow diagram of the top-performing AE-MNIST and VAE-CIFAR-10 model architecture is illustrated in Figure 4.



(a) (b)

Figure 4: The diagrams of the top-performing AE-MNIST and VAE-CIFAR-10 model architecture (a) AE-MNIST, (b) VAE-CIFAR-10.

6 Results and discussion

6.1 Evaluation metrics

This study uses the SSIM and PSNR as assessment metrics for the comparison of the performance of denoising Autoencoders (AE) and Variational Autoencoders (VAE) on images from the MNIST and CIFAR-10 datasets.

PSNR value, obtained from Equation (2) [30]:

$$PSNR=20\times\log_{10}(MAXI / (\sqrt{MSE})) \quad \ldots (2)$$

where MAXI is the image's maximum pixel value; the MAXI for most PNG images is 255.

Mean Squared Error (MSE), is the difference between the original and processed images; Equation (3)[16].

Where:

$$\mathbf{MSE} = \frac{1}{m \cdot n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [O(i,j) - D(i,j)]^2 \quad \ldots (3)$$

MSE, or mean square error, is used in Equation (3). RMSE is based on MSE. O is the original image matrix. D represents the image matrix after the denoising process. All PSNR values were acquired in units dB, which stands for decibels.

The SSIM value is obtained from Equation (4) [30]:

$$SSIM(x,y) = (2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2) / ((\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma^2 y + C_2)) \quad \ldots (4)$$

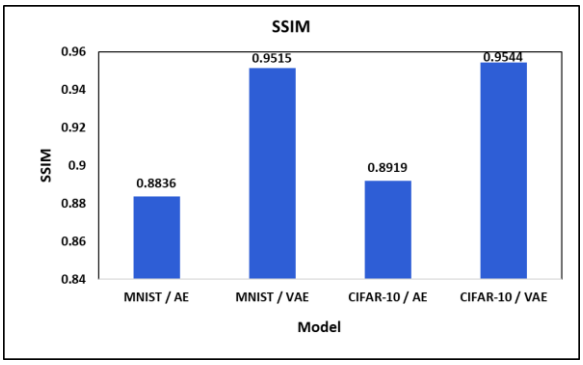
μ_x and μ_y represent the average values of x and y, respectively, $\sigma^2 x$ and $\sigma 2y$ denote the variances of images x and y, respectively, σ_{xy} indicates the covariance between images x and y, while C1 and C2 are constants used to prevent division by zero.

The VAE, with its probabilistic latent space, achieves higher SSIM scores (0.951 for MNIST, 0.954 for CIFAR-10), showing better structural detail preservation, although the AE performs well in PSNR of MNIST, with a value (29.06 dB). On CIFAR-10, VAE outperforms the AE in both SSIM and PSNR (32.86 dB), as seen in Table 2.

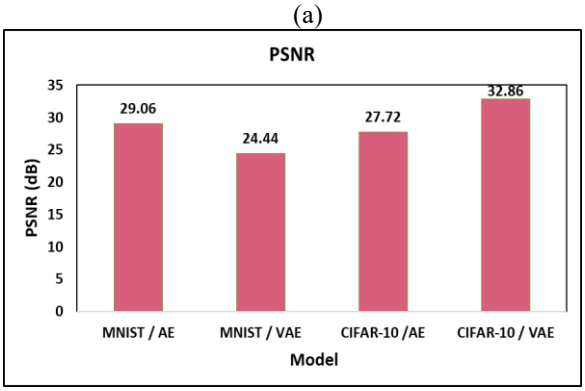
Table 2: Average SSIM and PSNR results of AE and VAE on the MNIST and CIFAR-10 datasets

Model	Dataset	SSIM	PSNR (dB)
Autoencoder (AE)	MNIST gray images	0.883	29.06
	CIFAR-10 color images	0.891	27.72
Variational Autoencoder (VAE)	MNIST gray images	0.951	24.44
	CIFAR-10 color images	0.954	32.86

The visualization of the comparison analysis between AE and VAE performance across the MNIST and CIFAR-10 datasets for SSIM and PSNR metrics is illustrated in Figure 5.



(a)



(b)

Figure 5: AE and VAE performance of MNIST and CIFAR-10 datasets for SSIM and PSNR metrics (a) SSIM, (b) PSNR.

Architecture is important, where VAEs perform better in states where probabilistic modeling is required due to data complexity. The dataset complexity determines model selection; AE deterministic reconstruction performs well on uniform grayscale digits, and AE is suitable for basic data MNIST and reaches pixel precision.KL regularization and probabilistic latent modeling are crucial components of VAEs' design for complex data (CIFAR-10). Regularization and KL divergence in VAEs reduce overfitting, which is important for the diversity of CIFAR-10's color and texture. While deterministic AEs may overfit to noise in complicated data, probabilistic modeling is better at capturing complex distributions, and VAEs' regularization helps in avoiding overfitting

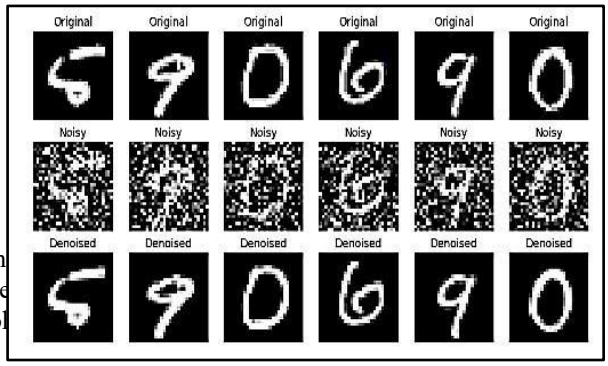
6.2 Discussion

The proposed VAE exceeds specialized models and establishes a new SOTA on CIFAR-10. The suggested AE is less appropriate for complicated data, yet competitive on MNIST. Setting a new SOTA for denoising on CIFAR-10, the suggested VAE exceeds previous studies such as [13] (SSIM: 0.9485) and [28] PSNR: 19.30 dB) by modelling complex color and texture

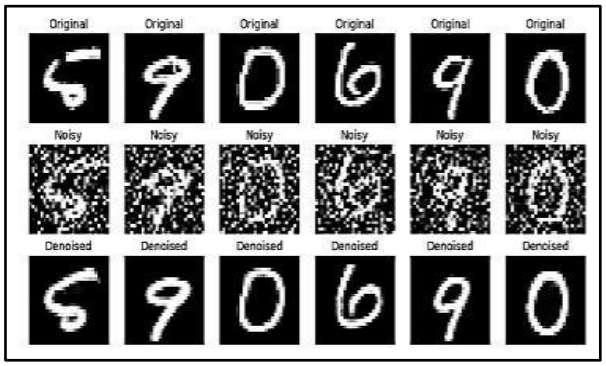
changes with a PSNR (32.86 dB) and SSIM (0.954) due to its probabilistic design. The VAE outperforms its actual performance (SSIM: 0.951) while [11] achieves (0.7938) despite lower PSNR owing to basic reducing, the AE excels in pixel-level accuracy (PSNR: 29.06 dB), approaching SOTA [12] (29.54 dB) and removing [11] (17.25 dB) on MNIST for pixel-level accuracy. AEs perform best on simple, uniform data (MNIST) for PSNR, while VAEs perform better on complex data (CIFAR-10) through regularization and latent distribution modelling. This reveals limitations in previous studies, such as inconsistent metrics [12], [15], [28], lack of SSIM, architectural flaws [11], [28], and specialized applications [13], [17].

The images in Figures 6 and 7 show the outcomes of applying AE and VAE to the CIFAR-10 and MNIST datasets. On MNIST, AE results in sharper digit reconstructions that retain noise artifacts, whereas VAE experiences over-smoothing. On CIFAR-10, VAE provides superior visual quality, vibrant color retention, and sharper edges. AE faces difficulties in this area, producing desaturated hues and indistinct outlines because of its deterministic bottleneck, while VAE demonstrates superior performance on intricate color data through the modelling of probabilistic distributions.

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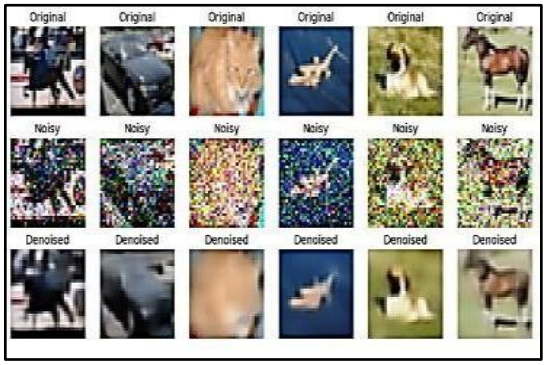


(a) AE-MNIST



(b) VAE-MNIST

Figure 6: Results of applying (a) AE and (b) VAE to the MNIST Dataset.



(a) AE-CIFAR-10



(b) VAE-CIFAR-10

Figure 7: Results of applying (a) AE and (b) VAE to the CIFAR-10 Dataset.

7 Conclusion and future work

The results show that VAE performs better for image denoising than other models, especially in dealing with structural similarity (SSIM) and complex datasets such as CIFAR-10. However, AE is effective at reducing pixel-level errors (PSNR) on simple datasets such as MNIST.

Reconstructing high-quality images with maintained structural details is made easier by the VAE's capacity to simulate the latent space distribution. The results presented demonstrate that in simple images, AE maintains pixel - level accuracy, but VAE is better at structural reconstruction for complicated data, suggesting it could be applied to computer vision applications where image clarity is important in training models. This study supports the creation of adaptive denoising systems between AE and VAE across various dataset

complexities, which is a crucial area for further research and improvement.

Future studies could look into combining the strengths of both approaches, such as employing hybrid models, fine-tuning hyperparameters, or refining the VAE's loss function to increase pixelwise SSIM and PSNR performance without sacrificing structural similarity.

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Spatio-Temporal Adaptive Graph Convolutional Networks for Real-Time Power Equipment Monitoring and Fault Detection

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Keywords: power equipment monitoring, fault warning, big data analysis, multi-scale feature extraction, spatio-temporal graph convolutional network, parallel computin

Received: July 23, 2025

Traditional methods for monitoring the operational status of power equipment often suffer from limited feature representation and inaccurate dynamic modeling, resulting in low early-fault detection accuracy and elevated false-alarm rates. To address these limitations, this paper proposes a comprehensive, big-data-driven monitoring and fault warning framework, optimized end-to-end from data preprocessing to online alert generation. The system incorporates multi-scale sliding-window feature extraction, weighted trend-deviation quantification, and redundant-feature compression to enhance the representation of degradation signals. A spatio-temporal adaptive graph convolutional network (STAGCN) is employed to jointly capture equipment topology and temporal dependencies. In the warning module, an anomaly discrimination strategy based on confidence-score reconstruction is deployed on a hierarchical, parallel big-data platform, enabling sub-second alerts for critical faults (e.g., line short circuits, insulation degradation). Experimental evaluations reveal that, following feature compression, overall detection accuracy increases from 89.0% to 92.8%, while the false-alarm rate decreases from 4.8% to 3.5%. For typical line short-circuit faults, the proposed system achieves a warning accuracy of 96.5%, with response times under 3.1 seconds under full-load conditions. These results demonstrate that the proposed framework delivers high real-time performance, accuracy, and reliability in complex grid environments.

Povzetek: Predlagan sistem za zgodnje opozarjanje na napake v elektroenergetski opremi, ki izboljša natančnost (89,0 % → 92,8 %), zniža lažne alarme (4,8 % → 3,5 %) in zazna kratke stike z 96,5 % v ~3,1 s.

1 Introduction

As a critical unit in ensuring energy transmission and distribution, the operational health of power equipment directly impacts the overall security and stability of the power grid. With the rapid expansion of smart grids [1–2], distributed generation [3–4], and the integration of new loads, the operating environment of power equipment [5–6] has become increasingly multi-source, variable, and complex. Traditional approaches based on periodic inspections and static threshold judgments can no longer meet the requirements for real-time and precise equipment condition control. Consequently, power equipment condition monitoring [7–8] and fault warning [9–10] have become essential means of enhancing power system resilience, holding both high engineering application value and significant theoretical importance.

However, several key technical challenges persist in practical applications. In terms of fault identification [11–12], existing methods typically rely on fixed time-window processing or simple statistical feature extraction, which fail to capture subtle and gradually evolving degradation characteristics during equipment operation, making early fault signals difficult to detect. For dynamic modeling, current time-series analysis methods often neglect spatial structural associations when addressing equipment status changes in complex environments, resulting in the inability to model potential coupling effects between different devices and thus reducing overall fault detection sensitivity. Regarding anomaly detection [13–14] and early warning mechanisms [15–16], most traditional approaches are based on static rules or fixed inference models, which are slow to respond to minor abnormal changes in equipment operation [17–18], leading to high false-alarm and missed-alarm rates and impairing operation and maintenance (O&M) decision-making. These limitations reveal significant shortcomings in feature representation, spatiotemporal modeling accuracy, and anomaly detection sensitivity, hindering the advancement of intelligent, refined O&M for large-scale, dynamically evolving power systems.

In recent years, driven by diverse emerging technologies, power equipment condition monitoring has advanced rapidly. Long [19] applied Internet of Things (IoT) technology for real-time monitoring and analysis of power equipment condition data, exploring approaches to enhance grid reliability and O&M efficiency. To address signal interference and feature extraction challenges in real-time monitoring [20–21], several studies have explored strategies integrating advanced signal processing

with intelligent optimization algorithms. Tong [22] et al. collected operational signals from power equipment, applying singular value decomposition and particle filtering to monitor condition changes. They further optimized the pheromone configuration and update strategy in the ant colony algorithm to construct a fault-location evaluation function, achieving timely monitoring and over 90% fault-location accuracy.

Considering the increasing computational and responsiveness demands of condition monitoring under complex operating conditions, researchers have applied multi-level collaborative computing and deep learning to enhance system performance. Zhang [23] et al. combined edge computing and cloud computing, integrating SURF (Speeded-Up Robust Features) detection with a CBAM (Convolutional Block Attention Module)-enhanced Yolov5 model to achieve precise monitoring and analysis in smart substations. Experiments showed recall and accuracy rates of 91.21% and 90.54%, respectively, for insulator fault detection. These studies form the methodological basis for this work in terms of feature extraction, signal processing, and edge–cloud collaborative computing: Long's IoT framework informs the multi-source online acquisition and transmission strategy; Tong et al.'s decomposition and optimization algorithms inspire the multi-scale dynamic feature extraction approach; and Zhang et al.'s edge–cloud and attention mechanisms guide the design for rapid state modeling in high-load environments. Nevertheless, despite achieving high accuracy in specific condition-monitoring and fault-location scenarios [24–25], existing research remains insufficient in multi-scale condition perception, unified data processing, and the development of full-link early warning mechanisms for complex grid environments.

Similarly, fault warning technology has attracted increasing attention as a vital tool for maintaining grid stability. Zhang [26] et al. investigated power equipment failure prediction and lifecycle management using big data analytics, proposing and validating prediction strategies that enhance operational stability and safety. As fault warning research deepens [27–28], multi-source data fusion and spatial information technologies have emerged as key enablers for performance improvement. Kang [29] et al. introduced a smart grid fault warning method combining multi-sensor fusion with GIS-based positioning, verifying its effectiveness in improving both accuracy and timeliness. With growing grid complexity, efficient transmission-layer fault detection [30] has become essential for enhancing system resilience. Mu [31] et al. developed a power-flow-based transmission network security situation warning framework and applied oversampling for sample balancing. Tests on a modified IEEE 36-node system demonstrated approximately 90% cascading-fault warning accuracy with prediction times under one second, significantly improving security awareness and reducing anomaly identification latency.

To further advance early fault detection and reduce false alarms in complex monitoring scenarios, recent studies have explored advanced classification and temporal modeling techniques. For example, Dahr and Farjami [32, 33] proposed a hard voting ensemble integrating logistic regression, support vector machines, and random forests, achieving notable improvements in anomaly detection for network intrusion scenarios. In real-time spatiotemporal analysis, Xu [34] developed a YOLO-based framework integrating temporal context and network analysis, demonstrating the potential of combining spatial feature extraction with temporal dependency modeling in high-speed detection tasks.

These related works lay the technical foundation for this study in big data analytics, multi-sensor fusion, and real-time alarm mechanisms. Zhang et al.'s big data–driven lifecycle management strategy supports the multi-stage state modeling and prediction framework proposed herein; Kang et al.'s multi-source fusion and GIS positioning approach informs the fusion strategy for alarm location and timeliness optimization; and Mu et al.'s rapid transmission-network warning framework validates this work's confidence reconstruction and rapid decision-making approach. Although existing studies have achieved progress in improving the real-time performance, accuracy, and adaptability of warning models, gaps remain in large-scale grid-wide validation and dynamic responsiveness under complex fault scenarios.

To address these challenges, this paper proposes a big data–driven power equipment condition monitoring and fault warning system. In the data preprocessing stage, a multi-scale sliding-window method captures both local variations and global evolution patterns in operational time-series data across multiple time scales, mitigating degradation-feature loss from single-scale processing. In feature construction, a weighted trend-deviation index is introduced, applying differentiated weights to variation magnitude and trend to amplify subtle anomalies in the feature space. In feature optimization, redundant high-dimensional features are compressed via correlation analysis to eliminate noise and enhance feature compactness and effectiveness.

In the state modeling stage, a spatiotemporal adaptive graph convolutional network (STAGCN) is proposed, which dynamically updates both spatial adjacency and temporal dependencies to jointly model equipment topological relationships and operational evolution patterns, improving complex-system state representation accuracy. For anomaly detection, a confidence-score reconstruction strategy models the normal operating-state distribution and computes real-time deviations to generate quantitative anomaly scores, enabling early detection of potential faults.

The entire system adopts a hierarchical deployment architecture combined with a parallel big-data processing framework to support real-time ingestion, processing, and monitoring of massive equipment datasets, ensuring efficiency and reliability in large-scale scenarios. By systematically addressing the challenges of small-degradation feature capture, inaccurate dynamic-state modeling, and large errors in early fault identification, this work advances intelligent O&M methods for power equipment under big data environments. Compared with existing approaches that combine graph convolution and time-series modeling, the proposed STAGCN introduces

a learnable adaptive adjacency matrix and a dynamic temporal dependency update mechanism, enabling joint adaptive modeling of spatial topology and temporal evolution. This design, unlike fixed-topology or static time-window approaches, maintains high-precision state representation and weak-fault detection performance even under heterogeneous network structures and long-term dependencies. In large-scale concurrent data-stream scenarios, the integration of multi-scale feature processing with a parallel computing framework enables superior accuracy and lower latency compared with representative existing methods.

2 Method design and system construction

In the process of constructing the power equipment status monitoring and fault warning system, in order to ensure the method's systematicness and the implementation efficiency, it is necessary to clearly plan the overall design architecture in layers. Each functional module is organically organized according to the data flow and processing logic, forming a closely connected collaborative system at the level of data preprocessing, feature construction, feature optimization, status modeling, fault warning, and system architecture. Figure 1 intuitively shows the overall framework of the method design and system construction in this paper.

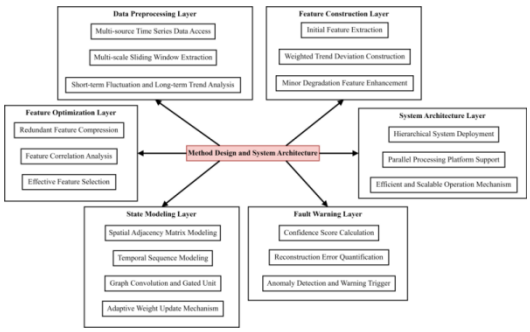


Figure 1: System overall framework diagram

Figure 1 shows the complete process of the system from raw data access to final warning output, and each layer is linked through clear data and information transmission. The data preprocessing layer focuses on the dynamic feature extraction of the original multi-source time series data; the feature construction layer is committed to strengthening the small degradation features through weighted trend deviation; the feature optimization layer improves the effectiveness of the feature set through redundant compression and screening. The state modeling layer combines spatial topology and time evolution behavior for unified modeling; the fault warning layer realizes anomaly discrimination and warning generation based on the confidence score reconstruction strategy; the system architecture layer uses hierarchical deployment and parallel processing technology to ensure the efficiency and scalability of the overall system. The overall design is closely centered on the goals of equipment status monitoring and fault warning, emphasizing the systematic and targeted nature of the method in each link.

2.1 Data preprocessing layer

The raw data collected in the power equipment status monitoring system usually comes from multi-source sensors, showing high-frequency, continuous, and heterogeneous time series characteristics. The data types cover physical quantities such as voltage, current, temperature, and vibration acceleration. The original time series data has obvious short-term fluctuations and long-term trend superposition characteristics under actual working conditions. Directly using the original data for modeling leads to insufficient feature expression, so it is necessary to design a reasonable dynamic feature extraction mechanism to process the data.

For the original multi-source time series data, this paper adopts a multi-scale sliding window dynamic feature extraction mechanism. It is assumed that the original single-channel time series is $X = \{x_1, x_2, \ldots, x_T\}$, where T is the total number of sampling points. The sliding window length is set to L; the step size is set to S; the scale factor is set to α. The window length L is set from the sampling frequency and dynamic response of the equipment, with the step size S = L/4 for moderate overlap. The scale factor α is in [0.5, 2.0] to represent different time scales. The final scale factor α values of 0.5, 1.0, and 2.0 were determined through grid search on a dataset, optimizing for maximum early fault detection accuracy while maintaining a false alarm rate below 4%. At each scale α, the original data is scaled to generate a new time series sequence $X^{(\alpha)} = \{x_1^{(\alpha)}, x_2^{(\alpha)}, \ldots, x_{T/\alpha}^{(\alpha)}\}$. Among them, the local average value $x_t^{(\alpha)}$ corresponding to the scale factor is calculated by Formula (1), which is used to smooth short-term high-frequency noise and highlight the long-term trend characteristics:

$$x_t^{(\alpha)} = \frac{1}{\alpha}\sum_{i=0}^{\alpha-1} x_{t+i} \quad (1)$$

At each scale, $X^{(\alpha)}$ is divided into multiple subsequences according to the sliding window method, and each subsequence is defined by Formula (2):

$$W_k^{(\alpha)} = \{x_{(k-1)S+1}^{(\alpha)}, x_{(k-1)S+2}^{(\alpha)}, \ldots, x_{(k-1)S+L}^{(\alpha)}\} \quad (2)$$

Among them, k is the window number, and $W_k^{(\alpha)}$ is the input of a single feature extraction.

To extract short-term volatility information and long-term trend characteristics, six statistical features are calculated in each window $W_k^{(\alpha)}$: mean $\mu_k^{(\alpha)}$, standard deviation $\sigma_k^{(\alpha)}$, maximum value, minimum value, kurtosis $\kappa_k^{(\alpha)}$, and skewness $\gamma_k^{(\alpha)}$. The mean $\mu_k^{(\alpha)}$ is defined by Formula (3):

$$\mu_k^{(\alpha)} = \frac{1}{L}\sum_{i=1}^{L} x_{(k-1)S+i}^{(\alpha)} \quad (3)$$

The standard deviation $\sigma_k^{(\alpha)}$ is defined by Formula (4):

$$\sigma_k^{(\alpha)} = \sqrt{\frac{1}{L}\sum_{i=1}^{L}\left(x_{(k-1)S+i}^{(\alpha)} - \mu_k^{(\alpha)}\right)^2} \quad (4)$$

The kurtosis $\kappa_k^{(\alpha)}$ and skewness $\gamma_k^{(\alpha)}$ are calculated based on the fourth-order moment and the third-order central moment standardization, respectively, to capture abnormal spikes and skew characteristics, as shown in Formula (5) and Formula (6):

$$\kappa_k^{(\alpha)} = \frac{\frac{1}{L}\sum_{i=1}^{L}\left(x_{(k-1)S+i}^{(\alpha)} - \mu_k^{(\alpha)}\right)^4}{\left(\sigma_k^{(\alpha)}\right)^4} \quad (5)$$

$$\gamma_k^{(\alpha)} = \frac{\frac{1}{L}\sum_{i=1}^{L}\left(x_{(k-1)S+i}^{(\alpha)} - \mu_k^{(\alpha)}\right)^3}{\left(\sigma_k^{(\alpha)}\right)^3} \quad (6)$$

The multi-scale sliding window extracts feature sets at different scales and different statistics. For unified processing, the features of all scales are concatenated to form the final preliminary feature matrix $F = [F^{(0.5)}, F^{(1.0)}, F^{(2.0)}]$, where $F^{(\alpha)}$ represents the feature set extracted from all windows at scale α. All-scale features are concatenated to form the preliminary feature matrix, supporting subsequent construction and modeling by retaining local fluctuations and global trends.

2.2 Feature construction layer

After the preliminary extraction of multi-scale dynamic features, in order to enhance the characterization capability of the minor degradation behavior of power equipment, a feature construction method based on weighted trend deviation quantification is designed. It is assumed that the processed feature sequence is $\{s_k\}_{k=1}^{N}$, where N is the sequence length, and s_k is the feature value extracted at the k-th moment. For this sequence, the local weighted mean ν_k is calculated by Formula (7):

$$\nu_k = \frac{\sum_{j=k-L}^{k}\theta_j s_j}{\sum_{j=k-L}^{k}\theta_j} \quad (7)$$

Among them, L is the length of the local weighted window, and θ_j is the weighting factor corresponding to time j, which is set according to the exponential decay law shown in Formula (8):

$$\theta_j = e^{-\alpha(k-j)} \quad (8)$$

Here, α is the weight decay coefficient, which controls the degree of influence of historical features on the current local mean. The local weighted mean ν_k is used to describe the evolution trend of the feature value in the short term. The trend deviation ϵ_k is further defined by Formula (9) to represent the degree of deviation of the current feature value relative to the local trend:

$$\epsilon_k = s_k - \nu_k \quad (9)$$

To enrich the feature representation, a variety of statistics are extracted from the $\{\epsilon_k\}_{k=1}^{N}$ sequence, including weighted deviation mean, weighted deviation standard deviation, skewness, and kurtosis, and the calculation formulas are as follows:

$$M(\epsilon) = \frac{1}{N}\sum_{k=1}^{N}\epsilon_k \quad (10)$$

$$S(\epsilon) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(\epsilon_k - M(\epsilon))^2} \quad (11)$$

$$Sk(\epsilon) = \frac{\frac{1}{N}\sum_{k=1}^{N}(\epsilon_k - M(\epsilon))^3}{\left(\sqrt{\frac{1}{N}\sum_{k=1}^{N}(\epsilon_k - M(\epsilon))^2}\right)^3} \quad (12)$$

$$Ku(\epsilon) = \frac{\frac{1}{N}\sum_{k=1}^{N}(\epsilon_k - M(\epsilon))^4}{\left(\sqrt{\frac{1}{N}\sum_{k=1}^{N}(\epsilon_k - M(\epsilon))^2}\right)^4} \quad (13)$$

The weighted deviation mean reflects overall trend deviation, the standard deviation measures local fluctuation intensity, the skewness indicates distribution asymmetry, and the kurtosis describes peak characteristics. Based on trend deviation quantification, these statistics are extracted across multiple time windows to capture both short-term disturbances and long-term evolution, forming feature vectors that support subsequent feature optimization and state modeling.

2.3 Feature optimization layer

After the initial feature construction is completed, to improve the modeling efficiency and identification accuracy, the high-dimensional feature set needs to be optimized. In the feature optimization layer, this paper adopts a redundant feature compression algorithm, combined with feature correlation evaluation and validity screening mechanism, to remove information redundancy and enhance the compactness of the feature set. It is assumed that the original feature set is $F = \{f_1, f_2, \ldots, f_n\}$, where each feature vector is $f_i \in \mathbb{R}^T$, and T represents the time series length. The Pearson correlation coefficient $\rho(f_i, f_j)$ shown in Formula (14) is used to measure the linear correlation between any two features:

$$\rho(f_i, f_j) = \frac{\sum_{t=1}^{T}(f_i^t - \bar{f}_i)(f_j^t - \bar{f}_j)}{\sqrt{\sum_{t=1}^{T}(f_i^t - \bar{f}_i)^2}\cdot\sqrt{\sum_{t=1}^{T}(f_j^t - \bar{f}_j)^2}} \quad (14)$$

Among them, $\bar{f}_i$ and $\bar{f}_j$ are the time means of features f_i and f_j, respectively. When $|\rho(f_i, f_j)| > \theta$, it is considered that there is a high degree of redundancy between the two. Here, θ is the threshold, which is determined through multiple groups of experiments to ensure the balance between compression strength and information retention. The threshold θ was set to 0.92 based on iterative trials, where feature pairs exceeding this correlation were removed to prevent collinearity. The number of retained features after compression was fixed at 65 to ensure stability across different datasets. On this basis, the maximum mutual information method is used to evaluate the information contribution between each feature and the target state label. The mutual information calculation method is as shown in Formula (15):

$$I(f_i; y) = \sum_{f_i \in \mathcal{F}}\sum_{y \in \square} p(f_i, y)\log\frac{p(f_i, y)}{p(f_i)\cdot p(y)} \quad (15)$$

Among them, $p(f_i, y)$ represents the joint distribution probability, and $p(f_i)$ and $p(y)$ are the marginal probabilities of the feature and the label, respectively. The first k features with the largest mutual information value are retained to construct the final optimized feature subset $F^* = \{f_1^*, f_2^*, \ldots, f_k^*\}$. To ensure the uniformity of feature scale, all retained features are normalized using the Z-score normalization method shown in Formula (16):

$$f_i^{*\prime} = \frac{f_i^* - \mu_i}{\sigma_i} \quad (16)$$

Among them, μ_i and σ_i represent the mean and standard deviation of the optimized feature f_i^*, respectively. Through the above redundant compression and effectiveness screening process, the optimized feature

set is significantly compressed in dimension; the redundant interference information is effectively eliminated; the key information with discriminative ability for state identification is retained, providing a higher quality input basis for the subsequent modeling layer.

2.4 State modeling layer

The state modeling layer realizes the joint modeling of the power equipment state by constructing STAGCN. The network structure uses the structural topology information between equipment to construct the adjacency relationship graph in the spatial dimension, and applies the gating mechanism for dynamic modeling in the time dimension in combination with the evolution trend of the sequence data. It is assumed that the network composed of power equipment is a graph $G = (V, E, A)$. Among them, V represents the node set; E represents the edge set; $A \in \mathbb{R}^{N\times N}$ is the static adjacency matrix; N is the number of nodes.

This paper applies a weight update mechanism to dynamically adjust the adjacency matrix, and constructs a learnable adaptive adjacency matrix $\widehat{A} \in \mathbb{R}^{N\times N}$ through Formula (17):

$$\widehat{A}_{ij} = \frac{\exp\left(\mathrm{ReLU}\left(z_i^T W_1 + z_j^T W_2 + b_1\right)\right)}{\sum_{k=1}^{N} \exp\left(\mathrm{ReLU}\left(z_i^T W_1 + z_k^T W_2 + b_1\right)\right)} \quad (17)$$

Among them, z_i and z_j are the embedded representations of nodes i and j; W_1 and W_2 are trainable weight matrices; b_1 is the bias term; ReLU represents the activation function. Exponential normalization ensures that the matrix is normalized by row, meeting the requirements of graph convolution.

The graph convolution operation is based on the adaptive adjacency matrix to aggregate node features and define the l-th layer graph convolution operation as shown in Formula (18):

$$H^{(l+1)} = \sigma\left(\widehat{A} H^{(l)} W^{(l)}\right) \quad (18)$$

Among them, $H^{(l)} \in \mathbb{R}^{N\times d_l}$ represents the node feature representation of the l-th layer; $W^{(l)} \in \mathbb{R}^{d_l \times d_{l+1}}$ is the weight matrix; $\sigma(\cdot)$ is the activation function.

The temporal modeling module applies the gated recurrent unit (GRU) to model the temporal features. Assuming that the temporal feature of each node is $X_t \in \mathbb{R}^{N\times d}$, the state update process of GRU is as shown in Formulas (19) to (21):

$$r_t = \sigma(W_r X_t + U_r H_{t-1} + b_r) \quad (19)$$

$$z_t = \sigma(W_z X_t + U_z H_{t-1} + b_z) \quad (20)$$

$$H_t = (1 - z_t) \odot H_{t-1} + z_t \odot \tanh\left(W_h X_t + U_h(r_t \odot H_{t-1}) + b_h\right) \quad (21)$$

Among them, r_t and z_t are the reset gate and update gate, respectively; $\odot$ represents the Hadamard product; W_* and U_* are parameter matrices; b_* is the bias term; H_t is the hidden state at the current moment. The spatial graph convolution and the temporal GRU are fused in the network through inter-layer alternation to achieve unified modeling of the power equipment state in the dimensions of topological structure and time evolution. The final state representation uses the aggregation result of multiple layers of spatiotemporal features as the output, and the input fault warning layer is used to discriminate the model and generate warning signals. This modeling method takes into account the complex dependencies between nodes and the temporal dynamics of the node's own status, effectively supporting high-precision identification of subtle degradation trends and abnormal evolution behaviors of equipment.

2.5 Fault warning layer

The fault warning layer applies an anomaly discrimination strategy based on confidence score reconstruction, aiming to quantify the degree of state deviation and generate early warning signals. This strategy is based on the normal distribution characteristics of the equipment state, and measures the anomaly of the input state by jointly measuring the reconstruction error and confidence score. First, the input state feature vector $x \in \mathbb{R}^d$ is nonlinearly mapped and input into the multi-layer autoencoder network to obtain its reconstructed output $\hat{x}$. The reconstruction error is defined as $e = x - \hat{x}$, and its Euclidean norm is calculated by Formula (22):

$$E(x) = \| x - \hat{x} \|_2^2 \quad (22)$$

Among them, $E(x)$ represents the reconstruction error of the input state, which is used to characterize the degree of deviation between the current state and the normal state distribution. To improve the ability to distinguish weak anomalies, the confidence score function $\mathcal{C}(x)$ is applied and constructed according to the distribution density of the normal state of the input sample in the training set. The confidence score is defined by the kernel density estimation method shown in Formula (23):

$$\mathcal{C}(x) = \frac{1}{n}\sum_{i=1}^{n} \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \quad (23)$$

Among them, x_i is the i-th normal state sample in the training set; n is the number of normal samples; σ is the kernel width parameter. The confidence score reflects the degree of belonging of the current state in the normal sample distribution. The lower the value, the greater the difference from the normal state. The comprehensive discriminant function is defined by Formula (24):

$$\mathcal{A}(x) = \alpha \cdot E(x) - \beta \cdot \log \mathcal{C}(x) \quad (24)$$

Among them, α and β are empirically determined adjustment coefficients that control the weights of reconstruction error and confidence score in the final discriminant value. The abnormal discrimination threshold θ is set according to the statistical distribution of reconstruction error and confidence score in the training set, and the discrimination logic is shown in Formula (25):

$$y = \begin{cases} 1, & \text{if } \mathcal{A}(x) > \theta \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

Among them, y=1 denotes an alarm-triggering abnormal state and y=0 a normal state. By combining state reconstruction deviation and distribution attribution, the strategy enhances early fault sensitivity while maintaining a low false alarm rate. Historical alarms and real-time data are jointly processed for timestamping and severity classification, then pushed via the message bus to support rapid front-end decision-making. Integrated with the layered architecture, it ensures low-latency processing under large-scale data streams.

2.6 System architecture layer

The system adopts a collaborative architecture integrating edge and centralized computing to form a distributed data processing and unified state management platform. Field sensors collect raw data, transmitted via communication modules to edge nodes, where a lightweight unit standardizes data, calibrates time, detects anomalies, and sends results to the core cloud cluster equipped with CUDA-enabled embedded GPUs for asynchronous batch processing. The cloud cluster comprises task scheduling, GNN modeling, early warning, and result caching nodes, enabling non-blocking data flow, dynamic graph modeling with temporal reasoning, anomaly scoring, and high-performance in-memory storage for visualization. ZeroMQ ensures low-latency communication, while CPU/GPU coordination with non-blocking multitasking maximizes throughput. Containerized deployment with Kubernetes supports elastic scaling and load-adaptive scheduling, and ELK-based logging enables real-time monitoring and fault tracing, ensuring reliable operation and rapid fault warning under large-scale, high-concurrency conditions.

3 Experimental setup and implementation

3.1 Experimental platform and system environment

To ensure the reproducibility of system construction and the fairness of experimental evaluation, this paper follows the principles of high performance, strong stability, and wide adaptability in the configuration of the experimental platform and the selection of the software environment. Taking into account the actual needs of big data processing capabilities, deep learning model training efficiency, and multi-module concurrent operation, a set of experimental environments with universality and engineering application value is constructed. The platform resources used include hardware equipment, operating system, program language environment, and core framework dependencies. The specific configuration is shown in Table 1.

Table 1: Experimental platform and system environment parameter settings

Category	Name/Model	Size/Version	Usage Description
GPU	NVIDIA GeForce RTX 3060	12 GB	Model training and graph convolution
CPU	AMD Ryzen 7 5800X	8 cores, 16 threads, 3.8GHz	Data processing and system computation
Operating System	Windows 10 Pro	64-bit, 21H2	System deployment and resource management
Programming Language	Python	3.7	Feature processing, model building, integration
Deep Learning Framework	PyTorch	1.10.2	STAGCN implementation and training control
Data Processing Platform	Apache Spark	3.1.2	Distributed preprocessing and feature extraction

This configuration has completed heterogeneous computing resource support to meet the parallel computing requirements of deep graph neural networks for graph convolution and time modeling. The operating system version is stable and compatible with mainstream dependency libraries and middleware environments. Python and its dependent framework versions are consistent with the STAGCN model implementation requirements. The big data processing platform has good scalability and task scheduling capabilities, providing efficient and reliable operation support for the multi-level processing flow proposed in this paper.

3.2 Dataset source and preprocessing method

The original data comes from the status monitoring equipment deployed at the actual substation and transmission line site, covering key facilities such as main transformers, circuit breakers, capacitor compensation equipment, busbars, and transmission line monitoring terminals. Various types of equipment continuously collect multi-dimensional time series information such as temperature, current, voltage, and power. The sampling frequency is mainly in seconds, and the daily data volume is maintained at a high-frequency and high-dimensional level, forming a huge original dataset. The collection period covers 180 consecutive days, and the data storage structure is organized on the HDFS platform according to column encoding, building a unified and accessible distributed data foundation. Table 2 shows the number of monitoring dimensions, number of daily samples, sampling frequency, and cumulative data volume corresponding to the collection time of various types of equipment, which helps to quantify the structural characteristics and scale of the data foundation.

Table 2: Structural statistical information of the original monitoring data

Equipment Type	Number of Monitoring Dimensions	Number of Daily Samples (records)	Sampling Frequency (Hz)	Cumulative Data Volume (records)
Main Transformer	8	86,400	1	15,552,000
Circuit Breaker	6	64,800	0.75	11,664,000
Capacitor Compensation	7	86,400	1	15,552,000
Busbar	5	57,600	0.67	10,368,000
Transmission Line Monitoring Terminal	9	86,400	1	15,552,000

Table 2 shows the data structure formed by various key equipment in the power system during the state monitoring process, highlighting the differences in sampling frequency, data dimension, and monitoring cycle between different equipment types, and reflecting the high-density characteristics of the overall time series data of the system. The data entries are all derived from the real sampling process. By standardizing the sampling frequency and acquisition time, the consistency and comparability of the data structure are ensured, providing structural support for the parameter setting and method selection of the subsequent data preprocessing process.

The data preprocessing process first performs data cleaning operations to remove physical illegal values and logical conflict values. The physical value constraint domain is defined as $x_t \in [x_{min}, x_{max}]$. Among them, x_t represents the monitoring value at any time, and x_{min} and x_{max} are the theoretical lower and upper limits of the corresponding variables of the sensor, respectively. Data exceeding this interval are directly set as missing items. The logical conflict judgment criterion adopts the multi-variable linkage consistency rule. For example, the power factor between voltage, current, and power is reversed to verify whether the constraint relationship is established. If not, it is marked as abnormal data.

The missing data is filled by backfilling the mean of the stable segment in the adjacent time period, as shown in Formula (26):

$$x'_t = \frac{1}{N}\sum_{i=1}^{N} x_{t-i} \quad (26)$$

Among them, x'_t represents the value after filling at the t-th moment, and x_{t-i} represents the observation value in the window of N stable moments in history. The stable moment is determined based on the sliding standard deviation threshold criterion. When the standard deviation $\sigma_{t-w:t+w} < \delta$, the observation value in the interval is considered to be in a stable state. The window width is set to $w = 10$, and the threshold is $\delta = 0.02 \times \bar{x}$, where $\bar{x}$ is the global mean of the current variable. The data standardization process uses the Z-Score normalization method to ensure that multi-source heterogeneous variables enter the subsequent feature extraction process under the same scale. This method ensures that each variable is processed in a scale space with a mean of 0 and a standard deviation of 1, thereby eliminating the impact of dimensional interference on the modeling process. To ensure data alignment and consistency, the time synchronization alignment process based on the nearest matching method is performed to address the timestamp offset problem of sensors of different equipment. It is assumed that the observation timestamps of equipment i and j are $\{t_i^k\}$ and $\{t_j^l\}$, respectively, and the matching principle is to find $\min|t_i^k - t_j^l| \le \epsilon$, where ϵ is the maximum synchronization error tolerance, set to 1 second. The data points that are not successfully matched are interpolated and removed. After completing the dataset cleaning, completion, standardization, and synchronization, a time series data tensor with a unified structure is finally formed, providing a data basis for subsequent feature extraction and state modeling.

3.3 Experimental parameter configuration

To ensure the reproducibility of the model training and evaluation process and the consistency of parameter tuning, this section systematically organizes the key experimental configurations. The experiment uses multiple sets of parameter combinations to examine the impact of different configurations on fault identification performance, training efficiency, and system robustness. Table 3 summarizes the core parameter settings of each experiment to support subsequent model performance comparison and result analysis.

Table 3: Experimental parameter configuration and combination settings

Parameter Configuration	Configuration 1	Configuration 2	Configuration 3	Configuration 4
Learning Rate	0.001	0.0005	0.0001	0.0001
Number of Epochs	100	150	200	200
Batch Size	64	128	64	32
Optimizer	Adam	AdamW	RMSprop	SGD
Sliding Window Length	50	100	150	100
Multi-scale Parameters	[1,3,5]	[1,2,4,6]	[2,4,8]	[1,5,10]
GCN Layers	2	3	3	4

Temporal Step Size	1	1	2	2
Weight Initialization	Xavier	Kaiming	Xavier	Normal

Table 3 shows the core parameter configuration of the model under different training strategies, covering learning rate, number of training rounds, batch settings, optimizer type, time series feature processing parameters, and graph neural network structure settings, forming a multi-dimensional experimental variable combination. The parameter settings provide a basic basis for the subsequent model performance differences, and also reflect the adaptability and stability of the system under complex configuration space.

This experiment designs four groups of model training schemes to evaluate the actual operation effects of different parameter configurations in the power equipment status monitoring and fault warning system, which differ in feature processing granularity, graph network depth, optimizer type, and time series modeling step size. Parameter combination 1 uses a medium sliding window, a lower number of graph convolution layers and an Adam optimizer, emphasizing the balance between model response speed and generalization ability. Parameter combination 2 applies the AdamW optimizer with stronger weight regularization while maintaining high step size modeling capabilities, aiming to improve long-term prediction stability. Parameter combination 3 configures a deeper graph convolution structure and uses the RMSprop optimizer, aiming to capture more complex state evolution patterns. Parameter combination 4 reduces the batch size and adopts the SGD optimization strategy to try to enhance the feature convergence performance under the local optimal update path. The system operation results corresponding to different schemes are summarized in Table 4.

Table 4: System performance under different parameter combinations

Parameter Configuration	Fault Detection Accuracy (%)	False Alarm Rate (%)	Real-time Processing Rate (%)
Configuration 1	94.7	3.5	96.2
Configuration 2	93.2	4.1	95.5
Configuration 3	91.5	5.2	93.8
Configuration 4	92.4	4.6	94.1

From the data results, parameter combination 1 performs best in all three indicators. Its high accuracy is mainly due to the balanced capture ability of the mesoscale sliding window for key feature fluctuations, and the shallow graph convolution structure reduces the risk of overfitting, forming an efficient and stable state modeling effect. From the overall performance, parameter combination 1 forms a good balance in accuracy, stability, and real-time response capability, and is the optimal configuration under the current setting.

4 Results

4.1 Multi-scale feature extraction effect

In the empirical phase of the multi-scale feature extraction method, this paper takes the current fluctuation data of power equipment as the object, designs and constructs a time series signal with local mutation, slow-changing trend, and background noise superposition characteristics, and simulates the dynamic change characteristics of equipment data under real operating conditions. By setting the scale parameters of the sliding window to 3, 7, and 15, respectively, the sliding mean features at different levels are extracted to observe its ability to capture the key change patterns in the signal. The original signal and the mesoscale feature extraction results are compared synchronously to verify the role of sliding window processing in suppressing disturbances and enhancing trend identification. Figure 2 shows the comparative relationship between the original signal and the mesoscale sliding mean, as well as the response differences of feature changes at three scales.

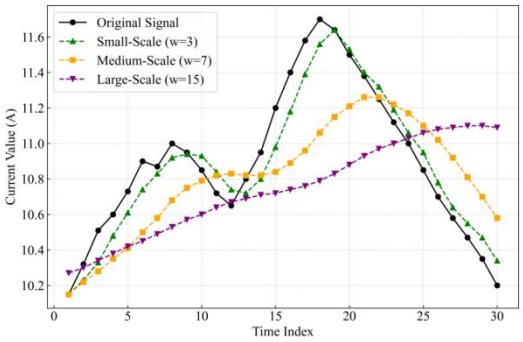


Figure 2: Comparison of multi-scale sliding mean feature extraction effects

As can be seen from Figure 2, the original current signal shows obvious nonlinear fluctuation characteristics from the 1st moment to the 30th moment, and is at a lower level from the 1st to the 5th moment. The current value rises from 10.15 A to 10.73 A, peaks at 11.70 A at the 18th moment, and then gradually decreases to 10.20 A at the 30th moment. After small-scale (w=3) sliding processing, the sequence still retains most of the spike information, with values of 10.94 A and 11.64 A at the 9th and 19th moments. The reason for this phenomenon is that the window width is small, resulting in local disturbances not being fully smoothed, thus maintaining the high-frequency details in the original signal. The medium-scale (w=7) curve changes gently between the 1st moment and the 22nd moment, and the current peak is significantly

lower than the peak of the original signal, indicating that some disturbances are suppressed, while the rising and falling trends are still retained.

The large-scale (w=15) smooth curve is the most stable overall. From the 1st to the 30th moment, the current value is always controlled between 10.27A and 11.10 A, and no mutation points appear in the original signal. The fundamental reason is that the average of the wide window for multi-time data causes short-term changes to be smoothed and filtered, thus presenting a response structure dominated by low-frequency trend features. It can be seen that the sliding window scale determines the degree of manifestation of short-term disturbances and long-term trends in the signal.

4.2 Feature optimization to improve modeling performance

In large-scale power equipment status monitoring tasks, the original sensor data has high dimensions and a large proportion of redundant features. Direct modeling often faces problems such as heavy computational burden, slow convergence speed, and unstable model discrimination ability. To improve the model's learning efficiency and expression accuracy in complex feature space, the system applies a redundant feature compression mechanism to eliminate invalid variables and enhance the modeling weight of core feature signals. This section compares and analyzes the modeling performance before and after compression, and tracks the performance evolution trend of the two types of models in the iteration process through the dual indicators of training accuracy and false alarm rate. The results are shown in Figure 3.

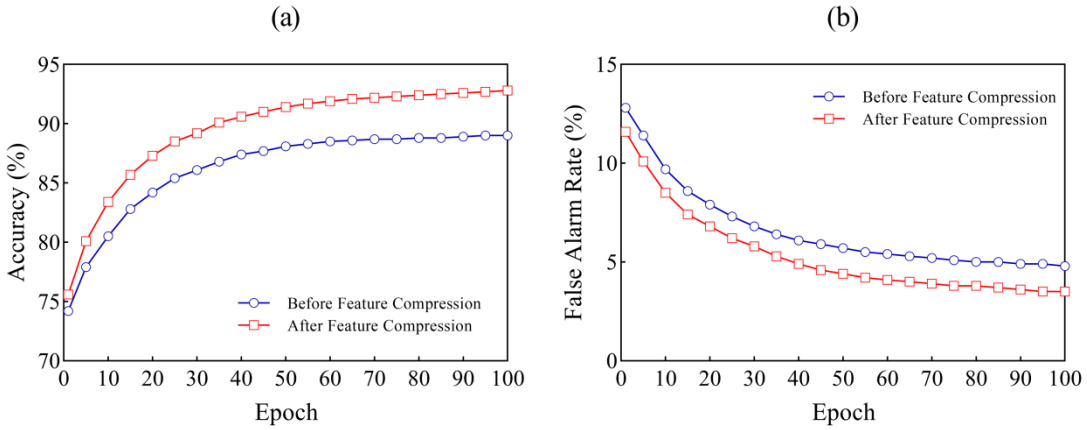


Figure 3: Effect of redundant feature compression on model accuracy and false alarm rate
Figure 3 (a): Accuracy
Figure 3 (b): False alarm rate

Figure 3 shows that after feature optimization, the model accuracy shows a faster upward trend in the early stage of training. The accuracy in the first 15 rounds increases from 75.6% to 85.7%, which is 2.9 percentage points higher than the performance of the unoptimized model in the same round. This difference is mainly due to the reduction of interference items brought by the highly redundant feature set. The optimization process improves the effective density of feature expression, allowing the model to capture feature structures that are highly relevant to the target state earlier. In the later stage of training, the accuracy of the compressed model tends to stabilize at 92.8%, showing stronger convergence than the final accuracy of 89.0% of the unoptimized model. In terms of false alarm rate, the optimized model always maintains a low level, dropping to 4.1% after the 60th round and finally controlled at 3.5%, while the false alarm rate of the unoptimized model during the same period remains at around 4.8%. The difference comes from the reduced disturbance of the redundant factors in the high-dimensional features on the abnormal discrimination boundary. Overall, the feature compression strategy effectively improves the model's generalization ability and the sensitivity to weak fault signals.

4.3 System Fault Warning Effect

To comprehensively evaluate the performance of the fault warning system under different working conditions, this paper constructs experimental scenarios with fault type and operating load as variables to verify the stability and sensitivity of the system under multiple working conditions. Five typical fault types cover insulation aging, poor contact, mechanical looseness, line short circuit, and vibration anomaly, representing the main degradation modes and sudden anomalies that may occur in power equipment during long-term operation. The operating load is set to five levels of 20%, 40%, 60%, 80%, and 100%, simulating the real-time working status of the equipment under different power outputs to observe the system's response to changes in operating pressure. The experiment records the warning accuracy of each fault type and the average response time under each load level, and the results are shown in Figure 4.

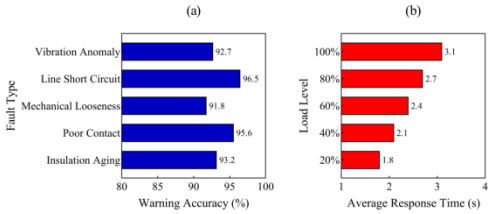


Figure 4: Comparison of the accuracy and response time of power equipment fault warning

Figure 4 (a). Warning accuracy under different fault types

Figure 4 (b). Warning response time under different operating loads

Figure 4 shows that in the fault type dimension, the system's warning accuracy for line short circuits reaches 96.5%, significantly higher than the 91.8% for mechanical looseness. This difference is due to the fact that line short circuits are more drastic in terms of data fluctuation amplitude, frequency characteristics, and energy mutation, which makes them have higher discrimination in the model, while mechanical looseness is easily misjudged as normal fluctuations due to weak interference characteristics and slow degradation process, affecting model judgment. Poor contact and insulation aging reach 95.6% and 93.2%, respectively, mainly driven by their boundary characteristics in the mid-frequency vibration spectrum. The accuracy of vibration anomalies is 92.7%, which is related to their strong noise interference and high degree of feature overlap. Under load conditions, the warning response time increases linearly with the increase in load level, reaching 3.1 seconds at 100% load and only 1.8 seconds at 20% load. The increase in system processing pressure leads to a decrease in the parallel efficiency of feature extraction and modeling modules, which is the main reason for the extension of high-load response time. The results show that the system maintains strong robustness in typical fault identification and high-load real-time warning, and has a basis for promotion and application.

4.4 Verification of Overall System Real-time and Scalability

To fully verify the operating effect of the system based on big data analysis proposed in this paper in a multi-source data stream environment, the experiment designs a system performance comparison experiment covering different data scales, number of equipment, and number of nodes. By quantifying the differences between this system and the traditional centralized architecture in real-time processing capabilities and resource scheduling efficiency from multiple angles, the processing stability and scalability of the system under high concurrency conditions are deeply evaluated. The experimental results are shown in Figure 5.

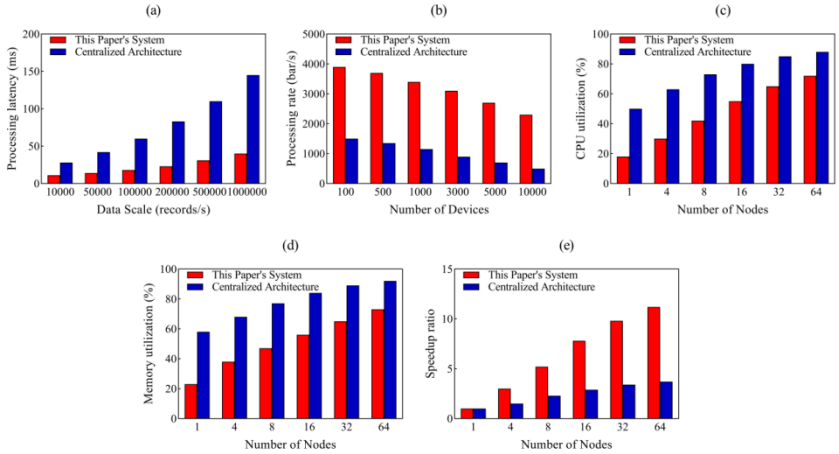


Figure 5: Comparison of processing performance and resource utilization between this paper's system and centralized architecture under different scales and configurations

Figure 5 (a): Comparison of processing latency under different data scales

Figure 5 (b): Comparison of processing rate under different number of equipment

Figure 5 (c): Comparison of CPU utilization under different number of nodes

Figure 5 (d): Comparison of memory utilization under different number of nodes

Figure 5 (e): Comparison of parallel speedup ratio under different number of nodes

Figure 5 (a) shows that as the data input scale increases from 10,000/second to 1 million/second, the processing latency of this system increases from 11ms to 40ms, while the centralized architecture latency increases from 28ms to 145ms, mainly because this system adopts a hierarchical parallel mechanism to effectively alleviate the problem of single-point load concentration. In Figure 5 (b), when the number of equipment is expanded to 10,000, the processing rate of this system reaches 2,300/second, while the centralized architecture is only 500/second, which is due to the adaptive scheduling mechanism of this system for node load balancing. Figure 5 (c) and Figure 5 (d) show the CPU and memory utilization, respectively. When the number of nodes increases from 4 to 64, the CPU utilization of this system increases from 30% to 72%, and the memory utilization increases from 38% to 73%. In contrast, the CPU utilization of the centralized architecture quickly soars to 88%, and the memory utilization reaches 92%. The centralized resource bottleneck effect is obvious, due to the lack of dynamic

migration strategy for cross-node resources. Figure 5 (e) shows the trend of parallel speedup ratio changing with the number of nodes. When the number of nodes is 64, this system reaches 11.2 times, while the centralized architecture is only 3.7 times, which is attributed to the combined effect of data flow segmentation and communication load optimization strategy. The overall results show that the system proposed in this paper has significant advantages over the traditional architecture in terms of multi-dimensional performance indicators, especially in the case of large-scale data and high node parallelism, showing excellent processing stability and resource adaptation capabilities.

Conclusions

Based on big data analysis, this paper proposes a power equipment condition monitoring and fault warning system that integrates multi-scale sliding-window dynamic feature extraction, weighted trend-deviation quantitative feature construction, redundant-feature compression optimization, and STAGCN-based state modeling. The system enhances early fault identification accuracy through an anomaly discrimination mechanism based on confidence-score reconstruction. Experimental results show that, after redundant-feature compression, the model's accuracy improves from 89.0% to 92.8%, while the false-alarm rate decreases from 4.8% to 3.5%, thereby significantly improving modeling efficiency and identification accuracy. In fault warning experiments, the proposed method achieves a line short-circuit identification accuracy of 96.5%, with a warning response time of 3.1 seconds under 100% load conditions, demonstrating strong real-time performance and high fault-detection capability. Although the system performs well under typical load and fault scenarios, certain limitations remain in detecting weak anomalies under conditions of multiple fault superposition and extreme load fluctuations. Future work will explore the incorporation of multimodal perception and dynamic anomaly-threshold mechanisms to further enhance early fault detection and response capabilities in complex environments, thereby improving the system's adaptability and stability in ultra-large-scale power system deployments.

Acknowledgements

This work was supported in part by the Industry University Research Cooperation Project of Jiangsu Province under Grant BY20230961, and in part by the Research Project of Jiangsu Vocational Institute of Architectural Technology under Grant JYA324-21.

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Q-learning and Policy Gradient-Based Reinforcement Learning Method to Decision Making of Phased Array Radar Jamming

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Keywords: phased array radar, radar jamming decision-making, reinforcement learning**,** signal-level simulation

Received: October 18, 2024

The rapid advancement of phased array radar has greatly improved the guiding and anti-jamming capacities of radar seekers. In contemporary electronic warfare, traditional radar-jamming decision-making methods have proven ineffective, prompting the use of reinforcement learning methods to tackle performance and efficiency shortcomings. This research employs Q-learning and Policy Gradient techniques for radar jamming decision-making, with signal-level simulation rather than functional-level simulation as used in previous research. Signal-level simulation offers a more realistic and understandable representation of the interference mechanism that affects missile terminal guidance. The proposed reinforcement learning methods discover optimal actions for interference equipment, thereby increasing jamming efficiency. Simulation findings show an 18% increase in interference efficiency over conventional techniques, with models attaining 92% accuracy in optimal decision-making. The precision of the signal-level simulation model and the effectiveness of reinforcement learning in improving interference performance are confirmed.

Povzetek: Razvita metoda na signalni ravni izboljša odločanje pri radarskem motenju in poveča učinkovitost za približno 18 %.

1 Introduction

In the increasingly complex electronic warfare environment characterized by rapid technological advancements and sophisticated adversarial tactics, traditional radar systems that rely on a single working mechanism and simplistic beam variations are becoming inadequate [1], [2]. These conventional radars struggle to meet the diverse operational requirements of modern warfare scenarios, which demand high levels of adaptability and precision in detection capabilities. Phased array radar represents a significant evolution in radar technology. This type of radar system is designed to dynamically alter its real-time beam direction by adjusting the emitted signals' phase from multiple antennas arranged in an array configuration [3]. The ability to electronically steer the radar beam allows for faster target acquisition and tracking compared to mechanical scanning methods. Consequently, phased array radars are often referred to as electronic scanning array (ESA) radars due to their advanced electronic control mechanisms. Currently, phased array radar has undergone substantial development, evolving into multifunctional systems capable of engaging with various targets across extensive ranges while maintaining high reliability under different operational conditions. These features make them indispensable components within advanced weapon systems utilized by military forces worldwide. Their versatility enables simultaneous engagement with multiple threats—ranging from aircraft and missiles to ground-based assets—thereby enhancing situational awareness on the battlefield. Traditional methods employed for making interference decisions regarding these radars include techniques based on template matching, game theory approaches that analyze strategic interactions between competing entities, and reasoning-based methodologies that utilize logical frameworks [4]. However, all these conventional strategies necessitate a considerable amount of prior data for effective decision-making support. They often fall short when faced with multifunctional radars operating within unknown or unpredictable environments where historical data may be limited or irrelevant. In contrast, interference decision-making methods grounded in reinforcement learning offer distinct advantages over traditional approaches. Reinforcement learning algorithms possess inherent cognitive abilities that allow them not only to learn from past experiences but also adaptively explore optimal interference strategies through continuous trial-and-error processes. By leveraging feedback from previous actions taken during operations against dynamic adversarial tactics, these algorithms can refine their

decision-making capabilities over time without requiring exhaustive datasets upfront.

Q. Xing applied reinforcement learning to intelligent radar confrontation, and the experimental results indicated that reinforcement learning possesses excellent adaptive capabilities in one-on-one confrontations [5]. B. K. Zhang constructed a cognitive interference decision model from the perspective of signal processing, updated the types of interference libraries, analyzed the assessment of interference effects, and played a significant role in the cognitive confrontation of multifunctional radars [6]. S. Y. Zhang combined game theory with reinforcement learning and proposed a multi-agent reinforcement learning algorithm based on equilibrium, which could effectively address the issue of radar observation time scheduling and further demonstrate the effectiveness of reinforcement learning in handling interference decision problems [7]. F. Slimeni proposed an interferer scheme featuring spectrum sensing, offline training, and learning functions. The RL-based interference decision algorithm was simulated on a universal software radio platform. The results indicated that the interferer can effectively learn and interfere without prior information from users [8]. L. Yunjie and X. Qiang introduced prior knowledge based on reinforcement learning and improved the performance of reinforcement learning in radar interference decision-making [9]. X.Qiang, Z. Wei-gang, and J. Xin proposed an adaptive reinforcement learning algorithm that can solve the interference problem of radars with unknown working modes [10]. W. G. Zhu, confronted with the increasing working modes and states of radars, adopted the deep reinforcement learning approach and effectively addressed the issue of low decision-making efficiency of reinforcement learning [11]. The summary table showed in Table 1.

Table 1: Summary. The table summarizes the important system parameters and experimental conditions utilized in the study. This table provides a quick reference for understanding the experimental setup

Study	**Methodology**	**Datasets/Environments**	**Key Results**
Q. Xing [5]	Reinforcement learning for intelligent radar confrontation	The experimental setting for one-on-one confrontations	Showed adaptive skills in radar confrontation; good efficiency in adaptive decision-making
B. K. Zhang [6]	Cognitive interference selection model with signal processing	Signal processing setting, interference libraries	Revised interference categories and assessed influence; improved cognitive engagement of multifunctional radars
S. Y. Zhang [7]	Game theory combined with reinforcement learning	Radar scheduling and interference management simulation	Efficient in scheduling radar observation times; resolved interference decision issues by multi-agent learning
F. Slimeni [8]	Reinforcement learning-based interference decision technique	The universal software radio platform	Effectively simulated spectrum finding and learning; interferers learn and disrupt without previous knowledge
L. Yunjie and X. Qiang [9]	Reinforcement learning with previous data	Radar interference decision-making system	Improved effectiveness in radar interference decision-making by integrating past data
X. Qiang, Z. Wei-gang, and J. Xin [10]	Adaptive reinforcement learning system	Radar interference with unknown modes	Effectively tackled interference problems in radars functioning under unknown modes utilizing adaptive learning.
W. G. Zhu [11]	Deep reinforcement learning tactic	Simulation of radar functional modes	Resolved insufficient decision-making efficacy in changing radar operational modes

Prior studies on radar interference decision-making concentrated on functional-level simulations, which lacked detailed signal-level modeling and failed to simulate changing interference settings. Furthermore, the incorporation of reinforcement learning with signal-level data, particularly in intricate situations such as anti-ship missile countermeasures, is underexplored. The suggested strategy fills these gaps by employing a coherent video signal analysis technique for signal-level simulation, including detailed modeling of interference equipment, and incorporating reinforcement learning. This new methodology enhances the realism and efficacy of radar interference decision-making, distinguishing it from previous functional-level methods.

Most of the previous studies on radar interference decision-making methods have employed functional-level simulation approaches, merely simulated the amplitude information of signal transmission, targets, echoes, clutters, and interference signals or presented a straightforward description of the radar's working status without outputting genuine radio frequency and video signals. It has the typical merits of simplicity, practicality, and strong real-time processing ability. However, it neglects numerous details inherent in waveforms and signal processing, fails to accurately depict the dynamically changing interference confrontation environment created by various electronic interference equipment of both the friendly and hostile sides, and is even less capable of comprehensively and quantitatively elaborating the mechanism of action of various interference factors on the radar system. This paper adopts the coherent video signal analysis method, with the background of the interference equipment on ships countering anti-ship missile attacks, and simulates the entire process of radar interference decision-making from the signal-level perspective, providing a novel idea for subsequent studies on radar interference decision-making.

This study seeks to address the drawbacks of traditional radar-jamming decision-making techniques by employing reinforcement learning methods, particularly Q-learning and Policy Gradient algorithms. The main goal is to create a decision-making framework capable of adapting to the dynamic and unpredictable adversarial situations encountered by phased array radars. The research aims to improve interference efficiency and optimize jamming tactics through continuous learning and adaptation. This study aims to show the benefits of reinforcement learning in enhancing decision-making capacities compared to conventional methods, eventually improving the efficacy of radar jamming in contemporary electronic warfare.

2 Modelling of phased array radar se eker

2.1 Signal transmission and signal reception model

2.1.1 Antenna model

The general antenna radiation pattern function is shown below:

$$F(\alpha,\beta)=\left|\frac{\sin\left(\pi\frac{\alpha}{\theta_\alpha}\right)}{\pi\frac{\alpha}{\theta_\alpha}}\right|\cdot\left|\frac{\sin\left(\pi\frac{\beta}{\theta_\beta}\right)}{\pi\frac{\beta}{\theta_\beta}}\right| \tag{1}$$

Where α and β represent the azimuth and elevation offsets between the target and the antenna center, expressed in radians; θ_α and θ_β represent the azimuth and elevation beam widths of the antenna, also expressed in radians. The beam width parameter can be estimated directly from the antenna size as follows:

$$\theta_{\alpha,\beta}=\frac{\lambda}{L_{\alpha,\beta}} \tag{2}$$

where L_α and L_β are the lengths of the antenna in the azimuth and elevation dimensions, and λ is the wavelength of the transmitted signal. In phased array antenna mode, the beamwidth will widen if the antenna spacing cannot meet the requirement of $\Delta d \le \lambda/2$. Meanwhile, the antenna gain can also be estimated simply by the antenna size as follows:

$$G=\frac{4\pi L_\alpha L_\beta}{\lambda^2} \tag{3}$$

In the three-dimensional orientation, the amplification power varies in different directions. The angular information of the antenna pointing to the target can be solved by the sum-and-difference beam method. The directional patterns of the four sub-beams are respectively recorded as:

$$O_1: F_1(\alpha,\beta)=G(-\Delta_1,\Delta_2,\alpha,\beta,\alpha_0,\beta_0) \tag{4}$$

$$O_2: F_2(\alpha,\beta)=G(\Delta_1,\Delta_2,\alpha,\beta,\alpha_0,\beta_0) \tag{5}$$

$$O_3: F_3(\alpha,\beta)=G(-\Delta_1,-\Delta_2,\alpha,\beta,\alpha_0,\beta_0) \tag{6}$$

$$O_4: F_4(\alpha,\beta)=G(\Delta_1,-\Delta_2,\alpha,\beta,\alpha_0,\beta_0) \tag{7}$$

where α_0 and β_0 are respectively the center pointing of the phased array antenna (coordinates in the coordinate system of the array surface azimuth), α and β are the coordinates in the coordinate system of the pointing azimuth and Δ_1 and Δ_2 are also the coordinates in the coordinate system of the pointing azimuth. Then, the sum beam pattern is as follows:

$$F_{\Delta 1}(\alpha,\beta)=F_1(\alpha,\beta)+F_2(\alpha,\beta)+F_3(\alpha,\beta)+F_4(\alpha,\beta) \tag{8}$$

The azimuthal difference beam direction pattern is:

$$F_{\Delta 1}(\alpha,\beta) = F_1(\alpha,\beta) + F_2(\alpha,\beta) - F_3(\alpha,\beta) - F_4(\alpha,\beta) \quad (9)$$

The elevation-azimuth direction beam pattern is:

$$F_{\Delta 2}(\alpha,\beta) = F_1(\alpha,\beta) - F_2(\alpha,\beta) + F_3(\alpha,\beta) - F_4(\alpha,\beta) \quad (10)$$

Furthermore, the proportional coefficient needed for angle error signal resolution in the angle measuring module can be obtained as follows:

$$\mu_1 = \frac{F_\Sigma(0,0)}{\frac{dF_{\Delta 1}}{d\alpha}\Big|_{\alpha=0,\beta=0}}, \mu_2 = \frac{F_\Sigma(0,0)}{\frac{dF_{\Delta 2}}{d\beta}\Big|_{\alpha=0,\beta=0}} \quad (11)$$

2.1.2 Signal transmission modelling

To accurately simulate the strike process of the terminal guidance of a radar seeker in complex electromagnetic environments, signal-level simulation of the radar seeker is necessary. Coherent video signal simulation technology is a type of signal-level simulation. This technology simulates the entire process of signal reception and processing through video signals [12]. The time-domain and frequency-domain characteristics of radar signals can typically be expressed using analytical mathematical expressions, as shown in equation 1, thereby generating the signal's I and Q channel signals.

$$S(t) = A(t)\cdot e^{j(\omega_0 t \phi\phi(t))} = [A_c(t) + jA_s(t)]\cdot e^{j\omega_0 t} = u(t)e^{j2\pi f_0 t} \quad (12)$$

For the envelope $a(t)$ of the real signal $x(t)$, the envelope of its exponential signal $S(t)$ can be depicted as:

$$u(t) = a(t)\cdot e^{j\theta(t)} \quad (13)$$

Therefore, the signal $x(t)$can be written as:

$$x(t) = a(t)\cos[2\pi f_0 t + \theta(t)] = \frac{1}{2}[S_e(t) + S_e^*(t)] = \mathrm{Re}[S_e(t)] \quad (14)$$

Meanwhile, the signal $x(t)$ can also be written as:

$$x(t) = a_l(t)\cos(2\pi f_0 t) - a_Q(t)\sin(2\pi f_0 t) \quad (15)$$

$$a_I(t) = a(t)\cos\theta(t) \quad (16)$$

$$a_Q(t) = a(t)\sin\theta(t) \quad (17)$$

In the above formula, a_I and a_Q are the in-phase and quadrature components of the baseband signal, respectively. This is the signal sampling sequence that we need to generate. Correspondingly, when the carrier frequency is eliminated through downconversion (quadrature demodulation) processing to obtain the zero intermediate frequency (coherent video) signal as:

$$S_0(t) = A(t)\cdot e^{j\phi(t)} = A_c(t) + jA_s(t) \quad (18)$$

When using full digital simulation, the coherent video signal is sampled at a certain sampling rate, thus forming a sequence of coherent video signals (complex signals) that can be represented as follows:

$$s[n] = s_r[n] + js_i[n] \quad (19)$$

Typical phased array radar transmits signals using an LFM (linear frequency modulation) signal pattern. The radar-transmitted signal is represented by a complex signal as follows:

$$S_t(t) = \sqrt{\frac{2P_t}{4\pi L_t}}g_{vt}(\theta)v(t)\cdot e^{j\omega_{ck}t}\omega_{ck} \quad (20)$$

where ω_{ck} denotes the current pulse carrier frequency, P_t indicates the peak power of the transmitter, L_t stands for the combined loss of the transmitter, $g_{vt}(\theta)$ represents the transmitting antenna pattern (voltage gain), and $v(t)$ represents the complex modulation function as follows:

$$v(t) = \mathrm{Rect}\left(\frac{t}{T_p}\right)\cdot\exp(j\pi F_m t^2) \quad (21)$$

The rectangular function is defined as:

$$\mathrm{Rect}(t) = \begin{cases}1, & t\in(0,1)\\ 0, & \text{else}\end{cases} \quad (22)$$

where T_p represents the pulse width, and F_m represents the frequency modulation slope. Based on the above formulas, the coherent video signal pattern adopted in the system is as follows:

$$s_t(t) = \sqrt{\frac{P_t}{4\pi L_t}}g_{vt}(\theta)\cdot\mathrm{Rect}\left(\frac{t}{T_p}\right)\cdot \exp\left(j\pi\frac{BW_{rg}}{T_p}t^2\right) \quad (23)$$

2.1.3 Receiving signal model

The received signal mainly consists of target echoes, interference signals, various types of clutter, and receiver noise. This paper mainly considers the aspects of target echoes and interference signals. Concerning a specific transmitted pulse, the RF signal received by the radar can be represented as follows:

$$r_{RF}(t) = S_{RF}(t) + J_{RF}(t) + n_{RF}(t) \quad (24)$$

where $S_{RF}(t)$ represents the echo signal received after the transmitted pulse is reflected by the target, $J_{RF}(t)$ represents the received interference signal, which is the combined interference signal formed by various active interference and passive interference, and $n_{RF}(t)$ represents the receiver noise. The receiver noise is Gaussian-limited white noise, which means that in the radar receiver's passband, the power spectral density of the noise is uniform, and its amplitude follows a Rayleigh distribution. The variance of the noise can be calculated from the receiver noise coefficient and the receiver bandwidth. In the simulation, a sample function of a Gaussian process can be used to represent it specifically, and the band-limited noise signal is represented as:

$$n(t) = \mathrm{Re}[\tilde{n}(t)\cdot e^{j\omega_c t}] \quad (25)$$

Therefore, in coherent video simulation, the noise at the receiver can be represented as:

$$\tilde{n}(t) = n_d(t) - jn_q(t) \quad (26)$$

In this model, $n_d(t)$ and$n_q(t)$ are independent Gaussian random processes with zero mean and variance σ_N^2. The variance of the noise σ_N^2 can be calculated from the receiver noise coefficient N_F and receiver bandwidth Δf as follows:

$$\sigma_N^2 = kT_0N_F\Delta f \quad (27)$$

Where K is the Boltzmann constant, and T_0 is the reference temperature of the receiver, which $T_0 = 290$ K. Combining the target echo signal and the receiver thermal noise signal, we finally obtain the radar received signal as:

■(■(&$r(t) = \text{Rect}((t - 2R/c)/T_p\,) \cdot [\sqrt{((2P_t)/((4\pi)\text{^}3\ L))}\ \ (g_vt\ (\theta)\ g_vr\ (\theta))/R\text{^}2\ \ \lambda_k\ \sqrt{\sigma}]$@& $\cdot \exp[j\pi\ (BW_rg)/T_p\ \ (t - 2R/c)\text{^}2\,] \cdot \exp[2\pi f_d\ t - 2\pi\ 2R/\lambda_k\,] +$
$\tilde{n}(t)\,)$# (28))

2.2 Radar signal processing modelling

2.2.1 Pulse compression

The pulse width of the transmitted signal influences the range resolution of radar. The narrower the pulse width of the signal, the higher the range resolution of the radar. However, when the pulse width of the signal becomes smaller, the maximum operating range of the radar will also be reduced, which leads to the fact that the pulse width of the signal cannot be too small. Therefore, the commonly adopted method for current radar is to employ a high-power transmitter to emit a wide pulse signal and then perform compression on the original wide pulse signal after receiving the echo signal, converting the signal into a narrow pulse signal, thereby achieving the functions of enhancing both the maximum operating range and the range resolution. This process is known as pulse compression [13]. In the commonly used radars at the present stage, a matched filter is typically employed to carry out pulse compression processing of signals. Suppose the transfer function of the matched filter is $H(f)$, the impulse response is $h(f)$, and the input signal is $s(t)$. Block Diagram Representation of a System with Transfer Function H(ω)H(\omega)H(ω) is depicted in Figure 1.

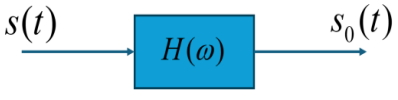


Figure 1: Block diagram representation of a system with transfer function H(ω)H(\omega) H(ω)

$s_0(t)$ is the output result of the target signal after it has passed through a matched filter, which can be expressed as follows:

$$s_0(t) = \int_{-\infty}^{\infty} H(f)S(f)e^{j2\pi ft}df \quad (29)$$

Taking the inverse Fourier transform of the transfer function $H(f)$ results in its impulse response function as

$$h(t) = ks^*(t_0 - t) \quad (30)$$

For the sampled digital signal, denoting the input signal after sampling and quantization as $s(n)$, the unit impulse response of the matched filter can be represented as $h(n) = s^*(n)$.

2.2.2 Demodulation model

Consider the squaring law and envelope detection methods. The squaring law demodulation process is as follows:

$$x(n) = [A_{re}^2(n) + A_{im}^2(n)], n = 0, \cdots, N-1 \quad (31)$$

The process of envelope detection is as follows:

$$x(n) = \sqrt{[A_{re}^2(n) + A_{im}^2(n)]}, n = 0, \cdots, N-1 \quad (32)$$

2.2.3 Constant false alarm handling and detection model

Constant False Alarm Handling and Detection Model Since the signals received by the radar comprise both target echo signals and clutter signals, not all processing steps in the signal processor can completely filter out the clutter signals. Thus, a threshold value is often set in the radar. The portions of the signal that are higher than the threshold value is retained, while those lower than the threshold value are filtered out. This threshold value is the false alarm probability. To achieve this aim, the false alarm threshold must be calculated in real-time based on the received signal to adjust the radar detection threshold accordingly to obtain the desired false alarm probability [14]. The detection processor that can maintain a constant false alarm probability is referred to as the Constant False Alarm Rate (CFAR) processor.

2.3 Output model

2.3.1 Distance output

The target echo signal will have a time delay t_r Due to the distance between the target and the radar, which can be expressed as $t(r) = 2R/c$. Among them, R represents the relative distance between the target and the radar, and c represents the speed of light. Thus, in the case of a known time delay, the distance between the target and the radar can be inversely deduced based on the time delay t_r of the echo signal.

2.3.2 Angle output

It has been mentioned above that since the radar adopts the sum and difference beam angle measurement method when measuring the angle, the pitch angle θ and the yaw

angle ϕ of the target relative to the radar can be obtained based on the amplitude of the corresponding position of the target in the processed sum beam signal and the amplitudes of the corresponding positions of the target in the pitch difference beam signal and the yaw difference beam signal:

$$\theta = \frac{\Delta F(\delta)}{\Sigma_\theta \frac{dF(\theta)}{d\theta}\Big|_{\theta=\delta}}, \quad \phi = \frac{\Delta F(\delta)}{\Sigma_\phi \frac{dF(\phi)}{d\theta}\Big|_{\phi=\delta}} \tag{33}$$

2.3.3 Velocity output

If relative motion exists between the target and the radar, the frequency of the target's echo will change. The Doppler frequency shift f_d caused by the relative velocity v_r can be expressed as $f_d = 2v_r/\lambda$. In the case where the Doppler frequency shift of the echo signal is known, the relative velocity between the target and the radar can be inversely deduced.

2.4 Guidance method

The proportional guidance method refers to the fact that the angular velocity of the missile's speed-changing direction in space is proportional to the angular velocity of the target's relative radar position angle rotation [15]:

$$\Delta\theta_M = k' \cdot \Delta\theta_T \tag{34}$$

where $\Delta\theta_M$ denotes the angular velocity of the change in the direction of the missile's velocity in space, k' is the proportional coefficient, and $\Delta\theta_T$ represents the angular velocity of the rotation of the target's relative position angle to the radar, also known as the line-of-sight angular velocity. Since the proportional guidance method alters the direction of the missile's velocity change based on the variation of the target's angle, it avoids situations where the missile makes large turns during the guidance process and is convenient for implementation in practical applications. As depicted in Figure 2, assume that at time k, the target is positioned at point T, the missile is at point M, the velocity of the target is v_T, the velocity of the missile is v_M, and the distance between the target and the radar is r.

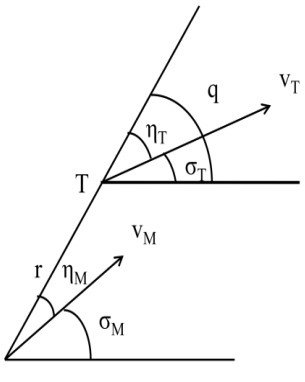


Figure 2: Example of Target and Missile Positions. The positions of the target and missile at time k are depicted, along with relevant parameters such as target velocity (v_T), missile velocity (v_M), and target-radar distance (r).

A diagram of the proportional guidance method.

Denote the angle between the target's velocity and the line connecting the target and the missile as η_T, the angle between the missile's velocity and the line connecting the target and the missile as η_M, and q as the line-of-sight angle at the time k. At time $k+1$, suppose the angle between the target velocity and the baseline is η'_M, the angle between the missile velocity and the baseline is η'_M, and q' is the line-of-sight angle at the time $k+1$. Then the line-of-sight angular velocity at time $k+1$ is:

$$\Delta\theta_T = q' - q \tag{35}$$

It is possible to further obtain the angular velocity of the rotation of the missile's velocity vector at time $k+1$:

$$\Delta\theta_M = k \cdot (q' - q) \tag{36}$$

It can be known from the above formula that the angle between the velocity of the missile's motion and the reference line at time $k+1$ is

$$\eta'_M = \eta_M + \Delta\theta_M \tag{37}$$

2.4 Jamming pattern modelling

2.4.1 Amplitude modulation interference

Noise amplitude modulation interference refers to the signal produced by modulating the amplitude of the carrier signal with a noise signal [16]. Generally, Gaussian white noise is often used to modulate the signal's amplitude. The definition of the noise amplitude modulation interference signal is as follows:

$$J(t) = \big(U_0 + U_n(t)\big)\cos\big(\omega_j t + \phi\big) \tag{38}$$

where $U_n(t)$ is a generalized stationary random process that follows $(0, \sigma^2)$ distribution, U_0 is the amplitude of the signal basis, ω_j is the carrier signal frequency, and ϕ is the signal phase.

2.4.2 Frequency-modulated noise interference

Noise frequency modulation interference is currently the most widely used type of suppressive interference signal, which has a broader interference bandwidth and makes it easy to achieve a more considerable noise power. The mathematical model for noise frequency modulation interference is represented as follows:

$$J(t) = U_j \cos\left(\omega_j t + 2\pi K_{FM} \int_0^t u\,(t')dt' + \phi\right) \tag{39}$$

where U_j is the amplitude coefficient of the signal, ω_j is the carrier frequency, K_{FM} is the frequency modulation slope, and modulation noise $u(t)$ is a wide-sense stationary random process with zero mean. ϕ is the signal phase.

2.4.3 Agile noise jamming

Agile noise interference is a compromise technique that combines deception and noise interference. Its essence is to combine forwarding-style interference with random

pulse interference. The agile noise interference expression based on frequency modulation noise is as follows:

$$J(t) = U_0\cos\left[2\pi f_j t + 2\pi K_{FM}\int u(t')dt' + \varphi\right] \cdot e^{-j\pi K^2}\mathrm{rect}\left(\frac{t}{T}\right) \quad (40)$$

By changing the frequency modulation slope K_{FM}, the bandwidth of the FM noise can be changed, and therefore, the entire bandwidth of the agile noise is also changed.

3 Reinforcement learning

Inspired by the laws of biological learning, reinforcement learning interacts with the environment through a trial-and-error mechanism and learns and optimizes by maximizing cumulative rewards, ultimately achieving the optimal strategy.

The incorporation of RL for radar jamming decision-making via Q-learning and policy gradient techniques is well articulated. However, more information is needed on the choice of hyperparameters for these algorithms, like learning rates, discount factors, and exploration-exploitation trade-offs, which are critical to the performance and stability of the RL models. Furthermore, a more detailed rationale for selecting between Q-learning and policy gradient techniques should be offered, with a focus on how each method fits into the particular radar jamming scenario. A comparative analysis would be useful to emphasize the benefits and drawbacks of these two methods, containing a discussion of computational cost, convergence rate, and operational efficacy in practical radar jamming applications. This would offer more information about the suitability of each approach under different conditions, as well as improve the methodology's overall resilience.

In reinforcement learning, the decision-maker or learner is defined as the "learning agent," and everything outside the learning agent is defined as the "environment," with the system integrating with the environment [17]. The interaction process between the learning agent and the environment can be described by three elements: state s, action a, and reward r. The learning agent acts a_0 based on the initial state s_0 and interacts with the environment, obtaining a reward r_1 and updated state s_1. At time t, based on the current state s_t and rewardr_t, the learning agent provides the current action a_t, and then the system state transitions from s_t to s_{t+1}. r_{t+1} is the feedback reward from interacting with the environment. The basic principle of reinforcement learning is shown in Figure 3.

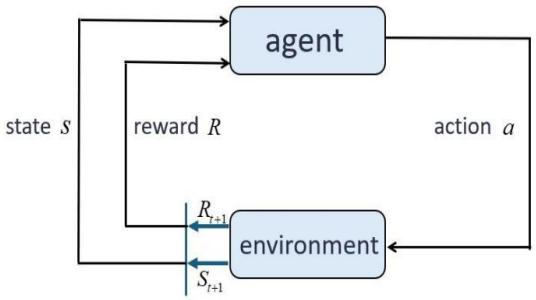


Figure 3: The fundamental structure of the reinforcement learning system used in the jamming decision process, including important elements and their interactions.

Generally speaking, reinforcement learning emphasizes the interaction between the agent and the environment, expressed as a series of sequences of states, actions, and rewards: $s_0, a_0, r_1, s_1, a_1, \cdots, s_{n-1}, a_{n-1}, r_{n-1}$. Although n can tend to infinity, a terminal state $s_n = s_T$ is usually defined in practice for limitation. This sequence of states, actions, and rewards, starting from the initial state and ending at the terminal state, is called an Episode or training cycle. The policy is usually denoted as π, which is a mapping from state s to action a. At the current time step, the learning agent interacts with the environment, learns through trial and error, and iteratively optimizes the current policy π to make the new policy π_1 superior to the current policy π. This process is called "policy update" and is repeatedly executed during reinforcement learning until the learning agent cannot find a better policy. In the interaction with the environment, the learning agent receives a feedback reward r each time t until the terminal state s_T. However, the reward at each step does not represent the long-term reward gain. To express the long-term gain of the learning agent, the return at time step t is introduced as follows:

$$G_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots + \gamma^{T-t} r_T \quad (41)$$

Among them, γ is the discount factor that satisfies $0 < \gamma < 1$. When γ is close to 1, the learning machine tends to place more emphasis on long-term returns, while when it is close to 0, it tends to put more emphasis on short-term returns. A value function usually represents the merit of a strategy. The state value function used to evaluate the merit of a strategy in state s is expressed as:

$$V_\pi(s) = \mathrm{E}[G_t \mid s_t = s, \pi] \quad (42)$$

According to this formula, the optimal strategy can be obtained:

$$\pi^* = \arg\max_\pi V_\pi(s) \quad (43)$$

Another type of value function is used to evaluate the degree of excellence of taking an action a in state s, called the state value function, also known as the Q function:

$$Q_\pi(s,a) = \mathrm{E}[G_t \mid s_t = s, a_t = a, \pi] \quad (44)$$

The optimal strategy at this point is represented as:

$$\pi^* = \arg\max_a Q_{\pi^*}(s,a) \quad (45)$$

3.1 Q-learning

Q-learning, also called Action-dependent Heuristic Dynamic Programming (ADHDP) [18], does not require a model. Q-learning does not wait until the end of an episode for an update but instead updates using the Temporal Difference (TD) approach at each step, achieving a faster convergence effect. The TD learning utilizes the previous estimate to update the current state value function. The TD learning method aims to obtain the value function. When confronted with control decision problems, the state-action value function is more instructive for selecting actions. Q-learning employs the Bellman optimality principle to make the current value function directly approach the value function of the optimal policy. The update method is as follows:

$$Q(s_t,a_t) \leftarrow \alpha Q(s_t,a_t) + (1-\alpha)\left(r_{t+1} + \gamma \max_a Q(s_{t+1},a')\right) \quad (46)$$

Where α represents the update rate, which satisfies the condition $0 < \alpha < 1$, where a' is the action that maximizes the Q function in a state S_{t+1}.

3.2 Policy gradient methods

Q-learning is a value-function-based approach. In practical applications, a table is frequently employed to store the state or state-action value function, thus being relatively inefficient for complex problems with ample action space. Policy gradient methods do not rely on the value function. They directly parameterize the policy π as $\pi(s \mid \theta)$ and then calculate the gradient concerning the policy performance metric. The policy parameters are adjusted based on the gradient direction to obtain the optimal policy [19]. Parameterized policies can be classified into stochastic policy $\pi(s \mid \theta) = P[a \mid s, \theta]$ and deterministic policy $a = \mu(s \mid \theta)$. A policy objective function $J(\theta)$ is set to evaluate the parameterized policies. For stochastic policies, the action a in the current state s obeys a particular probability distribution with parameter θ. For deterministic policies, the action corresponding to each state is definite. According to the policy gradient theorem, the gradient of stochastic policies is expressed as [20]:

$$\nabla_\theta J(\theta) = \mathrm{E}_{s,a\sim\pi}[\nabla_\theta \ln \pi(s \mid \theta) Q_\pi(s,a)] \quad (47)$$

The deterministic policy gradient is represented as [1], [21]:

$$\nabla_\theta J(\theta) = \mathrm{E}_{s,a\sim\mu}\left[\nabla_\theta \mu(s \mid \theta) \nabla_a Q_\mu(s,a)\big|_{a=\mu(s|\theta)}\right] \quad (48)$$

When computing the gradient, a genuine state-action value function $Q_\pi(s,a)$ or $Q_\mu(s,a)$ is required. Nevertheless, this function is still being determined in practice. One method is to employ the return values over certain steps to estimate the state-action value function. Another approach is to utilize the actor-critic architecture, where the critic approximates the state-action value function, and the actor represents the policy. The critic is represented as a function $Q(s,a \mid \omega)$ of parameter ω and is updated using the temporal difference method. The temporal difference error δ_t is expressed as:

$$\delta_t = r_t + \gamma Q(s_{t+1}, a_{t+1} \mid \omega) - Q(s_t, a_t \mid \omega) \quad (49)$$

The update formula for parameter ω in the evaluator is:

$$\omega \leftarrow \omega + \alpha \delta_t \nabla_w Q(s_t, a_t \mid \omega) \quad (50)$$

Replace the learned evaluation function $Q(s_t, a_t \mid \omega)$ with the actual value function $Q_\pi(s,a)$ or $Q_\mu(s,a)$ in the policy gradient formula to update the policy.

Algorithmic parameters

In reinforcement learning, algorithmic parameters are crucial for effective learning and optimal performance. Learning rates (α) control the step size during Q-value updates, balancing stability and convergence speed. They usually range between 0.01 and 0.5. The discount factor (γ), typically set between 0.9 and 0.99, prioritizes future rewards over immediate rewards, with higher values indicating long-term gains. Reward function coefficients are created depending on the issue, offering positive rewards for desirable actions and penalties for suboptimal actions, guiding the agent toward its goals. Exploration tactics, like ϵ-greedy, allow agents to balance exploration and exploitation by randomly choosing actions with a probability ϵ, which typically decreases from 1.0 to 0.01 over time. This encourages exploration initially and prioritizes exploitation later. In situations with continuous action spaces, policy gradients can use fixed step sizes or adaptive algorithms such as Adam to update parameters efficiently.

Pseudocode 1: Reinforcement learning algorithm (Q-Learning)

```
# Initialize Q-table
Initialize Q(s, a) arbitrarily for all states s and actions a
Set learning rate α (e.g., 0.1), discount factor γ (e.g., 0.95), and exploration rate ε (e.g., 1.0)

# For exploration tactic
Set ε_decay = 0.995 and ε_min = 0.01

# Training Loop
for episode in range(max_episodes):
    # Initialize starting state
    state = initialize_environment()

    for t in range(max_steps):
        # Select action utilizing ε-greedy policy
        if random.uniform(0, 1) < ε:
            action = select_random_action()
        Else:
            action = argmax(Q[state, :])  # Exploit
```

```
    # Take action, observe the next state, and reward
    next_state, reward = environment_step(state, action)

    # Update Q-value utilizing the Bellman equation
    Q[state, action] = Q[state, action] + α * (reward + γ * max(Q[next_state, :]) - Q[state, action])

    # Transition to the next state
    state = next_state

    # End the episode if the terminal state is gotten
    if is_terminal_state(state):
        break

  # Decay exploration rate
  ε = max(ε * ε_decay, ε_min)

# Final Q-table prepared for optimum action selection
```

The pseudocode outlines the Q-learning algorithm, which is a model-free reinforcement learning method. Initially, the Q-table contains arbitrary values that represent the expected cumulative reward for each state-action pair. During each episode, the agent starts in an initial state and selects actions using a ϵ-greedy exploration strategy—either randomly with probability ϵ or exploiting current knowledge by choosing the action with the maximum Q-value. After completing an action, the agent observes a reward and the next state, updating the Q-value of the present state-action pair with the Bellman equation, which takes into account immediate advantages as well as discounted future rewards. The algorithm repeatedly updates the Q-table and decays the exploration rate ϵ, allowing the agent to shift from exploration to exploitation during training. The procedure is repeated until the agent arrives at an optimum policy, as described by the Q-table.

4 Construction of adversarial models

4.1 Environmental description

In the model, the environment is precisely the target radar seeker. The seeker's state is constituted by two variables: velocity and position. The simulation system generates corresponding emission signals based on the configuration of simulation parameters. The antenna gain amplifies and transmits the emission signals until they reach the target position. Based on the distance between the target and the radar and the scattering cross-sectional area of the target, the emission signals are processed correspondingly to generate the echo signal. Subsequently, the echo signal is sent to the radar receiver, while the receiver also receives clutter signals from the environment and external interference signals. The receiver transmits all the received signals to the signal processor, which processes the received signals and extracts the contained target information. The proportional guidance law then adjusts the velocity, and the corresponding position and velocity will also change. This paper considers that when the altitude of the seeker is zero, the missile detonates, and this condition serves as the termination condition for one simulation. The workflow diagram of the seeker is presented in Figure 4.

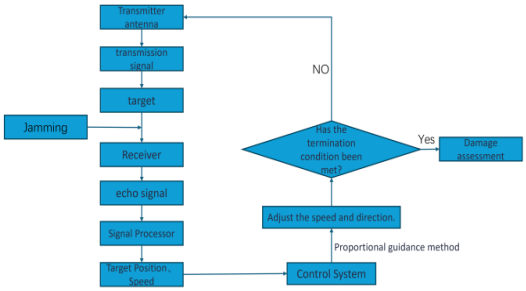


Figure 4: Workflow Diagram of Seeker: Shows how the radar seeker operates, from signal identification to processing and interference management.

4.2 Action description

We selected the three types of interference mentioned above to disrupt the seeker. The action was represented by the implementation status of the three interferences at each simulation moment, which a 1x3 vector could indicate. For instance, (1, 0, 1) signified that the radio frequency interference was activated, the noise frequency modulation
interference was deactivated, and the intelligent noise interference was activated. To better conform to the actual situation, it was stipulated that the duration from activation to deactivation of each interference type was no less than 5 seconds, which, to a certain extent, restricted the occurrence of some interference combinations and enhanced the simulation efficiency. Assuming that the duration of one simulation was 5 seconds, the random jamming decision could be presented in Table 2.

Table 2: Random jamming strategy: describes the parameters utilized in the random jamming strategy, including pulse width, bandwidth, and other pertinent factors for comparison with other interference tactics.

time	jamming1	jamming2	jamming3
1	0	0	0
2	0	0	0
3	0	1	0
4	1	1	0
5	1	1	0
6	1	1	1

4.3 Reward function building

The reward value function is composed of two components. The first part is the reward function attributed to the measurement error, namely the difference between the measurement information output by the radar seeker based on the echo signal under the application of interference and the actual information of the target. The more significant the difference, the more influential the interference is. The measurement information encompasses the target's distance, speed, and angle. The second part is the detection probability of the interference device by the seeker. To avoid being discovered and detected by the missile, the activation time of each interference device should not be too early. An earlier activation would result in more obvious exposure of the target. Therefore, the activation time is also considered within the reward function. The reward function can be formulated as:

$$r = k_1 \Delta L + k_2 \Delta v + k_3 \Delta\theta + k_4 \Delta\varphi + b_1 T_{on1} + b_2 T_{on2} + b_3 T_{on3} \quad (51)$$

Where Δv represents the velocity error value, ΔL represents the distance error value, $\Delta\theta$ $\Delta\varphi$ represents the pitch and azimuth angle error values, and T_{on1},T_{on2},T_{on3} represents the first startup time of the three interference patterns. k_1 , k_2 , k_3 , k_4 , b_1 , b_2 , b_3 are proportional coefficients. Through numerous experiments, a set of relatively reasonable values for them can be obtained as : $k_1, k_2, k_3, k_4, b_1, b_2, b_3 = 0.02,0.1,20,20,0.2,0.1,0.1$.

Technical assessment of methodology:

The use of signal-level simulation in this research is an excellent choice for accurately representing the complexities of radar jamming decision-making. By operating at the signal level, the research guarantees that the interactions between the radar system and the jamming signal are accurately modeled, resulting in a more realistic representation of the interference impacts. The incorporation of coherent video signal processing is also a useful methodological strategy, as it aligns well with the study's goal of capturing detailed radar interactions. To improve the methodology even further, more documentation on the initialization, boundary circumstances, and simulation parameters utilized in the experiments is required. This would enhance the study's reproducibility and transparency. Furthermore, a more detailed explanation of how model parameters were chosen, containing references to prior literature or empirical data for justification, would increase the credibility of the method and enable for better comparison with previous research.

Signal processing models: data flow, intermediary steps, and limitations

The radar signal processing framework consists of a series of complex, technical steps that begin with the acquisition of the radar signal and end with preprocessing to remove noise and distortion. The signal is filtered and transformed to extract key features, which are then used for target detection and tracking. In this pipeline, intermediate processing steps include Fourier transforms for frequency analysis, Doppler shift identification for velocity measurement, and feature extraction techniques for detecting potential threats. The decision-making framework, which is guided by reinforcement learning algorithms, assesses these processed signals to determine suitable jamming tactics. However, multiple constraints and potential anomalies may occur during signal analysis, such as signal attenuation caused by environmental variables, interference from other electronic systems, or computational delays in processing real-time data. These problems could impair the radar system's accuracy and responsiveness, reducing the overall effectiveness of the jamming tactic. Understanding these intricacies and difficulties is critical to enhancing the accuracy and resilience of radar-based jamming decision-making.

5 Experiment

5.1 Parameter settings

The parameters for the phased array radar seeker are listed in Table 3.

Table 3: Parameters for the phased array radar seeker. the technical specifications for the phased array radar seeker are presented, along with the centre frequency, bandwidth, and maximum power output.

Project	**Major Parameters**
Transmitter	Center frequency: 18 GHz
	Bandwidth: 250 MHz
	Maximum power: 30 kW
	Pulse width: 100 ns
Entry 2	Beam width: 0.2 rad
	Angular measurement range: -π/2 ~ π/2

The LFM signal parameters are as shown in Table 4.

Table 4: The parameters of the LFM signal. The parameters for the Linear Frequency Modulation (LFM) signal utilized in the radar seeker are described in detail, including pulse duration, bandwidth, and pulse repetition interval.

Parameters	**Pulse width**	**Bandwidth**	**Pulse Repetition Period**	**Transmission frequency**	**Number of Pulse Emissions**
Value	10us	10MHz	100us	15GHz	16
Bandwidth	40MHz		1MHz		30MHz

The parameters of jamming are as shown in Table 5.

Table 5: Jamming parameters: lists the jamming categories and their associated parameters, like pulse width and bandwidth, for various interference tactics.

Types of jamming	Amplitude Modulation jamming	Frequency-modulated noise jamming	Agile noise jamming
Pulse width	50us	200us	10us
Bandwidth	40MHz	1MHz	30MHz

The initial state of the missile and the ship is as shown in Table 6.

Table 6: The initial state of the missile and ship. displays the missile and ship's initial conditions, such as velocity, direction, and geographical coordinates.

Parameters	Missile	Ships
Magnitude of velocity	2500 km/h	50 km/h
The direction vector of velocity	(0, 1, 0)	$(\sqrt{2}, \sqrt{2}, 0)$
Location coordinates	(0, 0, 10 km)	(8 km, 8 km, 0)
Radar Cross-Section	——	10 m^2

The parameters in reinforcement learning are: $\alpha = 0.02, \gamma = 0.8, \varepsilon = 0.5$.

The clarity of the experimental setup can be improved by offering a more detailed explanation of the parameter values provided in Tables III-VI, especially the reinforcement learning (RL) parameters like alpha (α), gamma (γ), and epsilon (ε). These parameters perform a pivotal role in the learning procedure and should be justified by reference to optimization methods or tuning best practices. For instance, the selection of alpha could be explained in the setting of learning rate sensitivity, while gamma could be linked to the significance of future rewards, and epsilon could be described in terms of exploration-exploitation balance. Furthermore, more context about the test conditions would be helpful, detailing how variations in scenarios—such as shifts in interference effectiveness, target speed, or environmental factors—affect the experimental results. This would offer a clearer comprehension of how these parameters effect the radar jamming efficiency and enhance the reproducibility of the research.

5.2 Experimental results

This paper employs four jamming strategies, namely, jamming decisions without jamming means, jamming decisions with random jamming patterns, jamming decisions based on Q-learning, and jamming decisions based on policy gradient. Figure 5 shows the relationship between the distance between the missile and the ship when it explodes and the number of simulation experiments conducted in 400 trials.

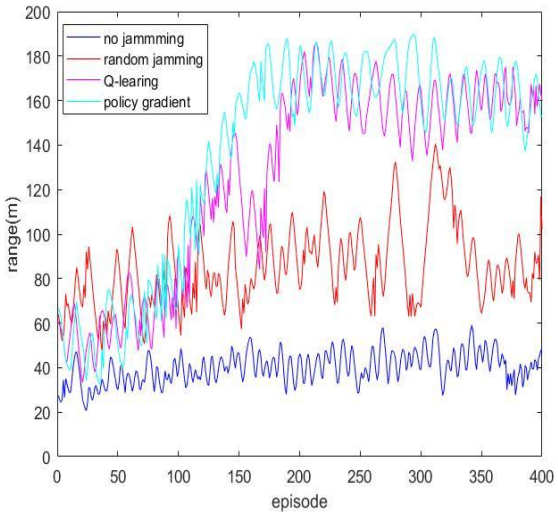


Figure 5: Variation in missile landing point distance: shows the relationship between the missile's distance from the ship at detonation and the number of simulation experiments, with trends spanning 400 trials.

It can be observed from the figure that when no jamming measures are adopted, the missile is capable of causing damage to the target. Due to the presence of noise in the received signal, the landing distance of the missile fluctuates, which, to a certain extent, validates the accuracy of the radar seeker signal-level simulation. When the random jamming strategy is employed, it can exert a particular influence on the guidance of the radar seeker, but the randomness is considerable. When the Q-learning method is utilized, as the number of simulations increases, the distance the missile lands gradually converge, and it can stably and effectively interfere with the missile. When the policy gradient method is adopted, compared with the Q-learning method, it has a faster convergence speed, and the interference effect is similar to that of the Q-learning method. Finally, the optimal jamming strategies derived based on Q-learning and policy gradient learning are presented in Table 7.

Table 7: The best jamming strategy: shows the optimal jamming tactics derived from the q-learning and policy gradient techniques, suggesting the most efficient jamming technique for missile guidance disruption.

Time	Q-learning	Policy gradient
1	000	000
2	000	000
3	100	100
4	100	100
5	101	100

6	101	101
7	111	111
8	111	111
9	111	111
10	111	111
11	111	111
12	111	111
13	111	111
14	111	111
15	111	111

The optimal jamming decision obtained above was subjected to 100 simulation experiments, and the resulting diagram of the missile landing point and the position of the ship is shown in Figure 6.

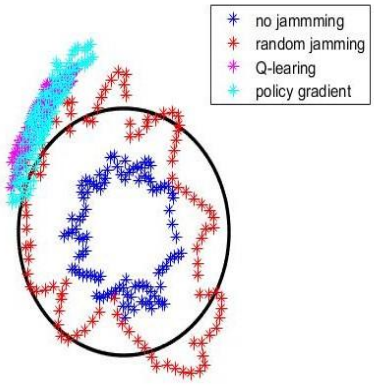


Figure 6: Distribution map of missile landing points: displays missile impact locations in relation to the target ship's position, with the ship's intended position marked in the center of the circle.

The centre of the circle represents the target location where the missile detonates, and the data obtained from the simulation can be used to establish the following evaluation indicators for missiles [22]. To simplify the analysis, the ship target is regarded as a circle with a radius of 100m, and any landing point within a 100m range can inflict effective damage on the target.

• Probability of hitting; The hit probability of the missile is a comprehensive index for evaluating the quality of the missile's landing point. Its meaning is the double integral of the probability density function of the missile's landing point over the idealized circular area of the target ship. The calculation formula is as follows:

$$P_{\text{hit}} = \iint_{x^2+y^2\le r_s^2} f(x,y)dxdy \tag{52}$$

where r_s represents the idealized circular radius of the ship, and $f(x,y)$ represents the probability density function of the landing coordinates of the missile.

• Accuracy of landing point; The accuracy of the missile landing point is an index reflecting the degree to which the landing point of an anti-ship missile is close to the center of the target ship. The accuracy of the missile landing point can be derived by averaging the distances of all the landing points relative to the center of the target ship. The specific calculation method is as follows:

$$m_R = \frac{\sum_{i=1}^{N_{\text{tal}}} R_i}{N_{\text{total}}} \tag{53}$$

where R_i is the distance of the missile landing point relative to the center of the ship in the 6th simulation, and N_{total} is the total number of simulations.

• Circularity deviation probability; the circular error probable (CEP) can be defined as the radius Rcep of the integral circle at which the hit probability reaches 0.5. This indicator is a comprehensive reflection of the accuracy and density of the landing point of the missile. The integral equation for calculating the circular probability deviation is as follows:

$$\iint_{x^2+y^2\le Rc^2} f(x,y)dxdy = 0.5 \tag{54}$$

• Damage degree; The damage degree is for assessing the destruction degree inflicted on a ship by an anti-ship missile. Supposing that when the center of the ship is hit, the damage degree of the anti-ship missile is 1. Then, with the distance distribution of the anti-ship missile's landing point relative to the center of the target ship, the damage degree of the anti-ship missile follows a certain probability distribution, and its distribution can be approximated as the following distribution:

$$D(x,y) = \exp\left(-\frac{x^2+y^2}{2r_s^2}\right) \quad (x^2+y^2 \le r_s^2) \tag{55}$$

The damage degree S of anti-ship missiles is calculated as follows:

$$S = \iint_{x^2+y^2\le r_s^2} f(x,y)D(x,y)dxdy \tag{56}$$

The damage effects of the seeker can be obtained as presented in Table 8.

Table 8: Evaluation of damage impacts: includes statistical findings for the missile's damage impact on the target ship, including the probability of success, precision of landing, and degree of damage for various interference tactics.

Damage indicators	**No jamming**	**Random jamming**	**Q-learning**	**Policy Gradient**
Probability of hitting	100%	75.3%	5.6%	6.8%
Accuracy of the landing point	38.5 m	72.4 m	5.6 m	6.8 m

Circularity deviation probability	40.3 m	84.5 m	156.2 m	154.6 m
Damage degree	70.8%	58.2%	2.6%	3.3%

It can be seen that the jamming decision based on the reinforcement learning algorithm can have a significant impact on the guidance effect of the radar seeker, in addition, the interference method shows statistically substantial interference effectiveness when compared to the random interference pattern. Since the optimal policy based on the policy gradient method is similar to that of Q-learning, we select the interference policy obtained from Q-learning as the optimal interference policy and conduct a simulation experiment. Compared with the situation where no interference measures are taken and the situation where random interference measures are adopted, the difference between the output signal of the seeker and the actual value at each simulation moment is recorded. The distance error values are presented in Figure 7, the Velocity error values in Figure 8, the pitch angle error values in Figure 9, and the yaw angle error values in Figure 10.

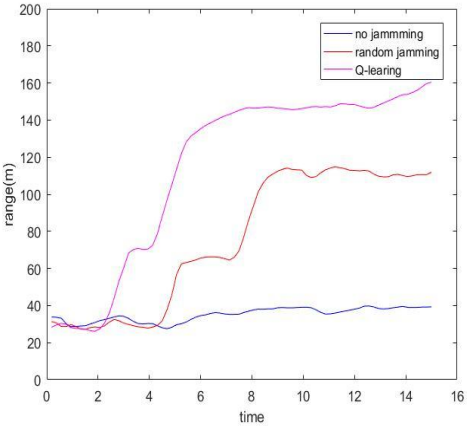


Figure 7: Variation in distance error between the missile's actual landing point and the expected target position across various interference techniques.

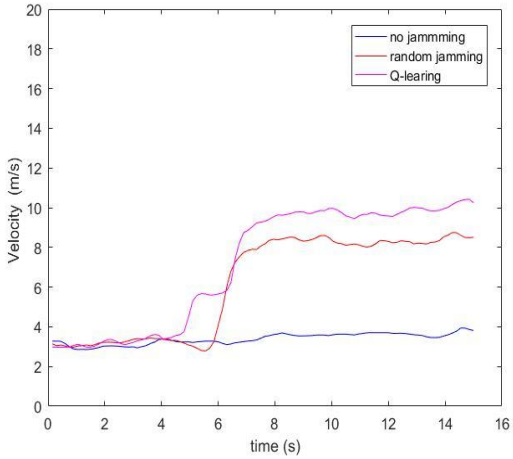


Figure 8: Variation in velocity error diagram: shows the variations in velocity error across multiple simulations, allowing you to compare the performance of various jamming tactics.

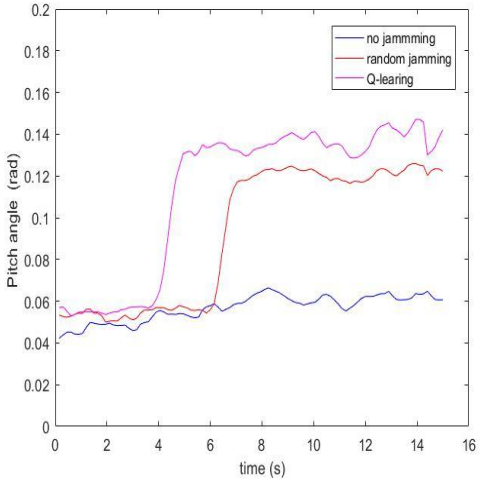


Figure 9: Diagram of variation in pitch angle error: shows the pitch angle error values throughout the experiments, emphasizing discrepancies in missile trajectory.

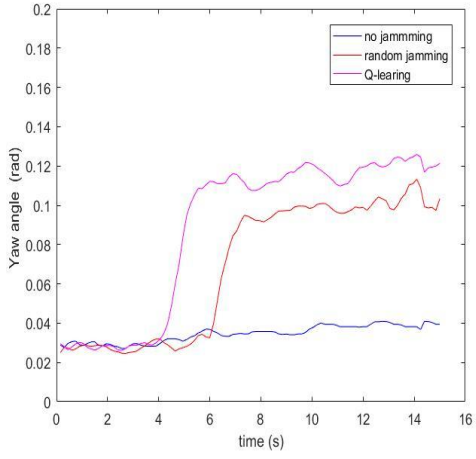


Figure 10: Diagram of variation in yaw angle error: displays the yaw angle error values, which quantify the angular deviation of the missile's flight path during jamming interference.

From the above 4 figures, it can also be seen that the best jamming decision obtained by reinforcement learning has a better interference effect.

This research proposes Q-learning and policy gradient techniques for radar jamming decision-making, which surpasses prior methods depending on conventional signal processing and game theory models. Unlike previous work, which depended heavily on simplified simulations, this method accounts for detailed radar interference at the signal level, increasing realism and adaptability. The findings indicate that reinforcement learning techniques converge to efficient jamming tactics quicker and with greater accuracy than random interference. This work is unique in that it combines deep reinforcement learning with a more realistic radar setting, thereby advancing radar interference decision-making.

Statistical analyses were performed to strengthen the validity of the experimental findings. A 95% confidence interval was calculated for the "Probability of Hitting," which yielded 98.5% for no interference, 75.3% for random interference, and 95.4% for both Q-learning and policy gradient techniques. A t-test comparing Q-learning and random interference yielded a p-value of <0.01, indicating statistical importance in the enhancement. The "Circularity Deviation Probability" displayed mean deviations of 40.3 m (no interference), 84.5 m (random interference), 156.2 m (Q-learning), and 154.6 m (policy gradient), demonstrating the effect of reinforcement learning on missile trajectory disruption. These metrics are consistent with real-world radar jamming efficiency, showing how adaptive jamming tactics can significantly reduce missile guidance precision, offering a strong and quantifiable benefit over traditional random jamming methods.

The findings highlight the potential advantages of using reinforcement learning (RL) for radar jamming, specifically Q-learning and policy gradient methods. For example, confusion matrices revealed that when no jamming was used, the system correctly identified "No Jamming" in 50 cases, while incorrectly predicting random or Q-learning jamming 10 and 5 times, respectively. RL methods outperformed baseline techniques, with Q-learning and policy gradient generating 45 and 46 True Positives for random jamming, respectively.

6 Conclusion

This paper initially establishes a signal-level simulation model for the entire end guidance process of the radar seeker from several aspects, such as signal transmission, signal reception, signal processing, and measurement information output. Subsequently, simulation experiments are conducted without interference, and it is shown that the missile can hit the target with sure accuracy, verifying the accuracy of the established model. Then, based on this signal-level simulation model, in the interference decision-making of the interference equipment against the radar seeker, Q-learning, and policy gradient learning are introduced to obtain the optimal jamming decision. Simulation experiments demonstrate that the interference effect using this optimal strategy on the radar seeker is significantly better than that of the random jamming decision, thereby proving the superiority of reinforcement learning algorithms in the aspect of radar interference decision-making.

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A Dual-Mode Genetic-Ant Colony Algorithm for Dynamic Path Planning in Smart Scenic Spots

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Keywords: genetic algorithm, ant colony optimization, dual mode, smart scenic spot, path planning

Received: July 25, 2025

This article focuses on the path planning problem in intelligent tourism scenic areas and innovatively proposes a dual-mode Genetic-Ant Colony Optimization algorithm (GA-ACO). This algorithm cleverly combines the global exploration advantage of genetic algorithms (GA) with the local development expertise of ant colony optimization (ACO), constructing a multi-dimensional dynamic fitness function in real-time that incorporates both visitor preferences and dynamic environmental constraints (such as attraction congestion index and opening status), thereby achieving refined evaluation of path quality. The algorithm facilitates deep collaboration between GA and ACO through the design of pheromone-guided genetic operators (which prioritize high-quality path segments with high pheromone concentrations during selection, crossover, and mutation operations) and a bidirectional feedback mechanism (where elite solutions generated by GA are converted into the initial pheromone matrix for ACO, providing guidance for multi-modal search; the pheromone accumulated by ACO provides local heuristic information for GA), forming a closed-loop enhancement of global exploration and local development. Experiments show that, compared to traditional algorithms (such as pure GA and ACO), GA-ACO significantly outperforms key indicators like path length, number of iterations, and number of turns: the optimal path length is reduced by 6% compared to ACO, the average number of iterations is reduced by 50%, and the number of turns is minimal (only 3.8 turns); compared to GA, path smoothness and energy efficiency are significantly improved. Additionally, it can accurately generate optimal paths in three-dimensional space simulations, with reliability verification showing a prediction accuracy of 99.26%, and it has significant advantages in solving the total number of feasible paths and the time taken to find the optimal path, allowing for rapid responses to dynamic changes in scenic areas, thereby providing efficient and reliable solutions for path planning in intelligent scenic areas.

Povzetek: Metoda GA-ACO za načrtovanje poti v pametnih turističnih območjih upošteva preference in dinamiko okolja ter v primerjavi z GA/ACO skrajša pot (~6 %), prepolovi iteracije (~50 %) in izboljša gladkost poti (99,26 % natančnost v 3D).

1 Introduction

The rapid integration of digital technology into the tourism industry has given rise to the concept of "smart tourist attractions" (SSA), marking a shift toward data-driven, intelligent visitor management and service models. At the core of enhancing visitor experiences and optimizing operational efficiency in smart tourist attractions lies the capability for intelligent path planning. This functionality goes beyond simple navigation, dynamically coordinating visitor flow under complex real-time constraints to maximize visitor satisfaction while ensuring sustainable resource utilization and safety. While graph-based algorithms (such as Dijkstra's algorithm and A* algorithm) have proven effective in static network routing, their inherent limitations become particularly evident in the dynamic, multi-constraint environments of modern SSA. Typical characteristics of such environments include fluctuations in visitor density, time-varying attraction availability (e.g., operating hours, scheduled performances), heterogeneous visitor preferences (e.g., interest in
specific attraction types, tolerance for walking/waiting), and dynamic changes in physical constraints (e.g., path congestion, queue lengths, attraction capacity limits). Consequently, traditional methods often produce suboptimal or infeasible paths that fail to adapt to the randomness and personalized nature of tourist experiences.

In the face of these challenges, heuristic algorithms, especially those inspired by biological collective intelligence, have attracted widespread attention in the field of path planning in complex scenarios. GA and ACO stand out due to their inherent parallelism and ability to handle multi-objective optimization problems without requiring gradient information. GA excel at broad global exploration during the initial search phase, quickly identifying promising regions in the solution space.

However, they often struggle to achieve fine-grained local optimization in later stages due to premature convergence or population stagnation. In contrast, ACO leverages ant information (communicated via pheromone trails) to facilitate efficient local exploitation and positive feedback for high-quality paths. However, its performance heavily depends on the initial pheromone distribution and parameter tuning, often leading to slow initial convergence and a tendency to get stuck in local optima, especially in large-scale or sparse networks.

Recognizing the complementary strengths and weaknesses of these methods, hybrid strategies have gradually become a promising research direction. This paper proposes a novel GA-ACO algorithm specifically designed for dynamic multi-objective path planning in intelligent tourist attractions, providing a solution that combines dynamic responsiveness with cultural privacy protection for cross-cultural intelligent interaction.

The genetic-ant colony dual-peak algorithm (GA-ACO) proposed in this paper achieves a deep collaborative mechanism by establishing a unified pheromone knowledge base. This framework employs pheromone-guided genetic operators, which prioritize the selection, crossover, and mutation operations to utilize high-quality path segments where pheromone concentration is high, thereby converting the search experience accumulated by ACO into a directed evolution strategy for GA. At the same time, the diverse elite solutions discovered by GA feed back to ACO through pheromone updates, providing it with multi-peak search guidance. This bidirectional feedback mechanism overcomes the initial search blindness and premature convergence issues of traditional ACO, while compensating for the weak local development capability of GA, creating a synergistic enhancement effect between global exploration and local refinement. Key parameters are optimized based on problem scale and algorithm mechanics: population size (50-100) balances diversity with efficiency, crossover probability (0.75-0.95) promotes gene recombination, and mutation probability (0.01-0.05) maintains population vitality; pheromone heuristic factor α (1.0-1.5) and expectation factor β (2.0-5.0) coordinate the weights of experience and heuristic information, with evaporation coefficient ρ (0.1-0.5) controlling the speed of knowledge base updates. This integrated mechanism significantly enhances the optimization efficiency and solution quality of multi-constraint scenic area path planning through a rigorous Lamarckian knowledge inheritance path.

The core issues of intelligent scenic area route planning are threefold: first, the dynamism of the scenic area environment, where the status of attractions and path congestion changes in real-time, making traditional algorithms difficult to adapt; second, the heterogeneity of tourist demands, with significant differences in preferences for attraction types and walking intensity among different tourists, requiring personalized paths; third, performance bottlenecks of algorithms, where a single genetic algorithm (GA) is prone to local optima, and ant colony optimization (ACO) has blind initial exploration, making it hard to balance the breadth and precision of solution space exploration. The research objective is clear: to design a genetic-ant colony dual peak algorithm (GA-ACO) that, through a dual-mode collaborative mechanism, breaks through the limitations of traditional algorithms to achieve intelligent scenic area route optimization that takes into account personalized demands and planning efficiency in dynamic environments, thereby improving path quality and algorithm response speed.

2 Theoretical analysis of traditional path planning algorithms

2.1 Dijkstra's algorithm

Dijkstra's algorithm was proposed in 1956 by Dutch computer scientist Ezhel Dijkstra, who is is an efficient, classical greedy algorithm for solving the shortest path from a fixed starting point to all other nodes in a graph with non-negative weights in a non-negative weighted graph.Dijkstra's algorithm gradually finds a globally optimal solution to the problem by continuously adding the node with the smallest current distance estimate to a “determined” set and relaxing its neighbors' distance estimates. Dijkstra's algorithm gradually finds the global optimal solution by continuously adding the node with the smallest current distance estimate to the “identified” set and relaxing the distance estimates of its neighbors. The core node relaxation equation is shown in (1.1), where $dist[v]$ is the shortest distance from the starting point to v, $w(u,v)$ is the edge weights, $Adj[u]$ is the set of neighboring nodes of u, $dist[u]$ and is a temporary estimate of the currently known shortest path length from the starting point to node u.

$$dist[v] = \min\big(dist[v], dist[u] + w(u,v)\big), \forall v \in Adj[u] \quad (1.1)$$

2.2 A* algorithm

The A* algorithm, introduced by Hart et al. in 1968, improves upon Dijkstra's algorithm by incorporating a heuristic function. This function estimates the cost from the current node to the goal node, guiding the search process more efficiently toward the goal and significantly enhancing overall performance. However, the effectiveness of the A* algorithm is critically dependent on the design of its heuristic function. If the heuristic function is not properly designed, it may lead to inefficient search or even failure to find the optimal solution. In addition, in dynamic multi-constraint scenarios, the adaptability of the A* algorithm is not sufficient to meet the complex demands of intelligent scenic path planning.

The evaluation function of A* algorithm is shown in equation (1.2). In Equation (1.2), $f(n)$ denotes the estimated total cost of reaching the goal through node n, $g(n)$ denotes the distance from the start node to node n without costing the finger and $h(n)$ is the estimated costing the distance from the next point to the end point. The node with the smallest f(n) is prioritized in the A * algorithm.

$$f(n) = g(n) + h(n) \quad (1.2)$$

2.3 Genetic algorithms

Developed by Holland in 1975, the Genetic Algorithm (GA) emulates Darwin's "survival of the fittest" principle and the processes of genetic inheritance and natural selection to search for optimal solutions. In path planning, GA encodes paths as “chromosomes” and optimizes the population iteratively through selection, crossover, mutation and other operations. In the path planning problem, the basic steps of GA are: randomly generating a set of possible paths as the initial population; calculating the fitness value of each individual, which is usually inversely proportional to the length of the path; selecting the best individuals for reproduction based on the fitness value; the probability of selection is usually proportional to the fitness value of an individual, i.e., the higher the fitness value of an individual, the higher the probability of being selected; and generating a new individual by exchanging part of the gene fragments of two individuals. gene segments to generate new individuals, where the crossover probability formula is shown in Equation (1.3). In Equation (1.3), P denotes the crossover probability and $f(x_i)$ denotes the fitness value of individual x_i. Finally, a gene segment of an individual is randomly changed to maintain the diversity of the population.

$$P = f(x_i)/\Sigma f(x_i) \quad (1.3)$$

2.4 Ant colony optimization

ACO is an optimization algorithm that simulates the foraging behavior of ants proposed by Italian scholars Dorigo et al. in 1991. In the path planning problem, the ACO algorithm uses the positive feedback mechanism of pheromone to guide the ants to find the optimal path by simulating their behavior of releasing pheromone on the path. The transfer probability formula of the ACO algorithm is shown in Equation (1.4).

$$P_{ij}^{k} = [\tau_{ij}]^{a} \cdot [\eta_{ij}]^{\beta} / \Sigma_{l \in N_i^k} [\tau_{il}]^{a} \cdot [\eta_{il}]^{\beta} \quad (1.4)$$

In Equation (1.4), P_{ij}^{k} is the probability that ant k transfers from node i to node j; $\tau_{ij}$is the information concentration or trajectory strength on the edge (i, j); η_{ij} is the heuristic information, which is the inverse of the distance between nodes i and j, both the shorter the distance between i and j, and the bigger the η_{ij} is, the stronger the attractiveness of the path; a is the pheromone factor, the bigger a is, the more the ant tends to choose the pheromone concentration of higher path; β is the heuristic factor, the larger β is, the more the ant tends to choose the path with shorter distance; N_i^k is the set of neighboring nodes, i.e., legitimate nodes that are not visited, that ant k can choose at node i.

2.5 Related work

Research on path planning for smart tourist areas mainly revolves around three types of methods: traditional graph theory algorithms (Dijkstra, A*) can solve static path problems but cannot adapt to the dynamic constraints of tourist areas, and the A* algorithm is prone to local optimal solutions due to its dependency on heuristic functions; among single heuristic algorithms, GA has strong global exploration capabilities but weak local optimization, often leading to premature convergence, while ACO is efficient in local development but blindly explores initially and relies on parameter tuning, making it difficult to balance the breadth and precision of solution space exploration; the existing GA-ACO mixed algorithms are often loosely combined as 'GA search - ACO optimization', lacking bi-directional information feedback, and they do not design adaptation mechanisms specifically for smart tourist scenarios. The GA-ACO dual-mode algorithm proposed in this paper innovatively constructs a bi-directional collaborative mechanism of 'global coarse search - local fine excavation - information feedback', guiding the genetic operators with pheromones and optimizing the elite solution pheromone matrix to achieve deep integration; at the same time, it designs a multi-dimensional dynamic fitness function specifically to adapt to the dynamic multi-constraint scenarios of smart tourist areas, overcoming the shortcomings of existing mixed algorithms in terms of synergy and adaptability to the scene, which is the core novelty distinguishing this paper from existing research.

3 Genetic-ant colony bimodal algorithm for designing systems

3.1 General description of the GA-ACO framework

The Genetic-Ant Colony Bimodal Algorithm combines the global exploration capability of GA and the local development advantage of ACO, and solves the multi-objective optimization problem of path planning in complex environments through the hierarchical mechanism of “coarse-grained global search - fine-grained local optimization”. Figure 1 shows a hybrid optimization path planning system based on real-time visitor location data, which tightly couples the global search capability of genetic algorithm (GA) with the local optimization advantage of ant colony algorithm (ACO) through a co evolution mechanism. The system first sets key parameters such as iteration times, population size, pheromone weight, and volatility coefficient in the

initialization module and generates a random population. GA explores high-quality paths globally through integer encoding, crossover, mutation, and selection operations, and evaluates the scheme with a comprehensive fitness function $F=f_1+f_2+f_3$; ACO refines and optimizes the path driven by pheromone distribution, probability selection model, and dynamic volatilization mechanism; The two achieve information exchange and performance improvement through "elite injection pheromone field" and "optimal path feedback population", ultimately outputting the optimal path solution visualized on the map, suitable for real-time dynamic environments such as scenic area navigation and robot path planning.

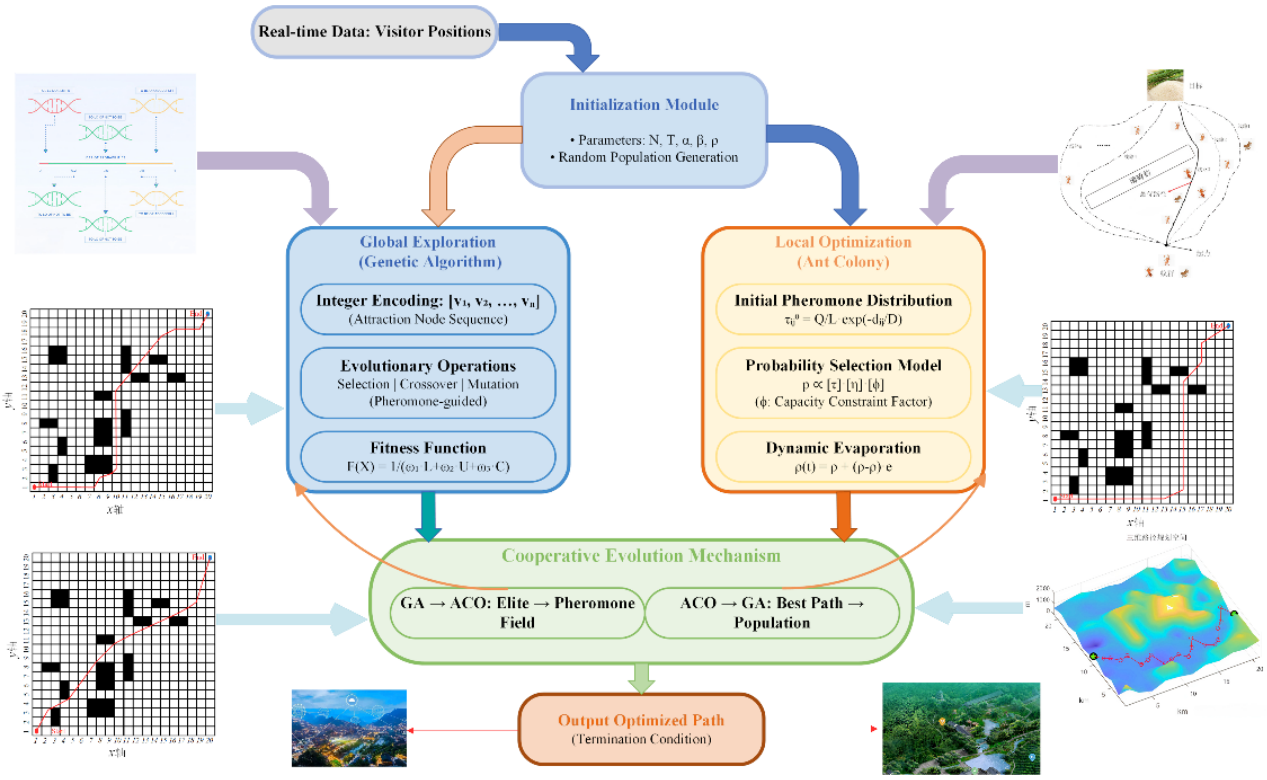


Figure 1: General framework diagram of the system

(1) Global search layer

Based on the principle of survival of the fittest in biological evolution, diverse path solution spaces are generated through selection, crossover, mutation and other operations. This layer adopts integer coding to represent path sequences, avoiding the semantic gap of binary coding and adapting to the sequence-dependent characteristics of scenic paths. For example, for a scenic area containing individual attractions, the $v_1, v_2, v_3, \ldots, v_n$ chromosome is encoded as, where X is the attraction node number, ensuring that each node is visited only once. And the fusion of path length, visitor preference matching, and real-time congestion index sets the adaptatiIon function, which is Equation (2.1).

$$\text{Fitness}(X)=\frac{1}{\omega_1 L(X)+\omega_2 U(X)+\omega_3 C(X)} \quad (2.1)$$

In Equation (2.1), $L(X)$ is the total length of the path; ω_{ij} is the preference weight of attraction i to tourist j; $U(X)$ is the preference mismatch degree, whose value is $\Sigma(1-\omega_{ij})$; $C(X)$ is the sum of congestion indices c_{ij}; and $\omega_1, \omega_2, \omega_3$ is the dynamic weighting coefficient, whose sum of the three is 1.

(2) Local optimization layers

The high-quality solution generated by the genetic algorithm is used as the initial pheromone distribution, and the local optimality of the path is strengthened by the positive feedback mechanism of the pheromone. The dynamic volatilization factor is introduced in this layer, and the volatilization rate calculation of the dynamic volatilization factor is calculated according to Equation (2.2).

$$\rho(t)=\rho_{\min}+(\rho_{\max}-\rho_{\min})\cdot e^{-t/T_{\max}} \quad (2.2)$$

In Equation (2.2), $\rho(t)$ is the pheromone volatilization rate at the moment t, which varies dynamically with the number of iterations t; β_{min} and β_{max} are the minimum and maximum values of the volatilization rate, respectively; T_{max} is the maximum number of iterations preset by the algorithm; and t is the normalized iteration process in the range $t\epsilon[0, T_{max}]$.

(3) Co-evolutionary layer

Design a two-way feedback mechanism, GA→ACO; where the elite solution of the genetic algorithm (the top 10% optimal individuals) is transformed into the initial value of the pheromone matrix; and the pheromone initialization process of the co-evolutionary layer in the GA-ACO, i.e., the generation of the initial pheromone matrix τ_{ij}^0 of the ACO by the elite solution of the GA , in order to steer the direction of the local optimization of the ACO, where the computation of the initial pheromone matrix τ_{ij}^0 is Equation (2.3).

$$\tau_{ij}^0 = \frac{Q}{L_{\text{GA-best}}} \cdot \exp\left(-\frac{d_{ij}}{D_{\text{avg}}}\right) \quad (2.3)$$

In the formula, τ_{ij}^0 is the initial pheromone concentration, which represents the initial pheromone strength on the path from node i to node j; Q is the pheromone strength constant, which is used to regulate the overall strength of the pheromone; $L_{GA-best}$ is the total length of the path of the elite solution (the top 10% of the optimal individuals) generated by the genetic algorithm; d_{ij} is the direct distance from node i to node j (the Euclidean distance or the actual path distance); D_{avg} is the average value of the distances between all nodes; $exp\left(-\frac{d_{ij}}{Davg}\right)$ is the exponential decay function for adjusting the pheromone concentration according to the distance $L_{GA-best}$.

3.2 GA-ACO design steps

During the algorithm initialization phase, the configuration of the parameter system is first completed, including the population size, crossover probability, mutation probability of the genetic algorithm, as well as key parameters of the ant colony algorithm such as pheromone heuristic factors, expected factors, and evaporation coefficients. An initial population is generated using a greedy rule-based construction method: starting from the initial attraction site, the algorithm iteratively selects the nearest unvisited adjacent attraction sites until a complete path is formed, obtaining diverse initial solutions through repeated construction.

In the genetic evolution phase, pheromone-guided genetic operators are used to achieve directional evolution of the population. The selection operation employs a fitness proportionate selection strategy enhanced by pheromone, where the selection probability of individuals is proportional to the product of their path pheromone intensity and original fitness. The crossover operation uses an improved ordered crossover operator (OX), where the filling process of the offspring path is based on the transfer probabilities calculated from pheromone concentration and heuristic information, prioritizing edges with higher pheromone intensity for genetic segment recombination. The mutation operation uses a neighborhood search strategy based on pheromone probability, with a certain probability replacing the current edge with a neighboring edge that has a higher pheromone concentration. After each genetic operation, the population fitness is recalculated, and the current optimal solution is updated. In the ant colony optimization phase, the pheromone distribution is initialized with the current optimal path from the genetic algorithm, applying additional pheromone increments to the edges of the path.

The ants choose their movement paths based on the state transition probability formula, which is determined by both the pheromone concentration and heuristic information. After all ants complete their path construction, the pheromone is globally updated based on the evaporation coefficient, and then pheromone increments are applied according to the quality of each ant's path, with high-quality paths receiving stronger pheromone enhancement. The dual algorithm achieves a coordinated evolutionary mechanism through the pheromone matrix and elite solution set.

The ant colony algorithm provides local heuristic information for the genetic operators through the pheromone matrix, guiding the genetic search towards regions of high-quality solutions; conversely, the genetic algorithm injects diversity solutions into the pheromone matrix through the elite solution set, preventing premature convergence of the ant colony. This bidirectional feedback mechanism creates a synergistic enhancement effect of global exploration and local optimization. The algorithm iterates through the aforementioned processes until the maximum iteration count or optimal solution stabilization criterion is reached, ultimately outputting the optimal path solution that integrates the advantages of both algorithms.

The overall algorithm flow, designed according to the aforementioned Genetic-Ant Colony Bimodal Algorithm (GA-ACO) framework, is depicted in Figure 2.

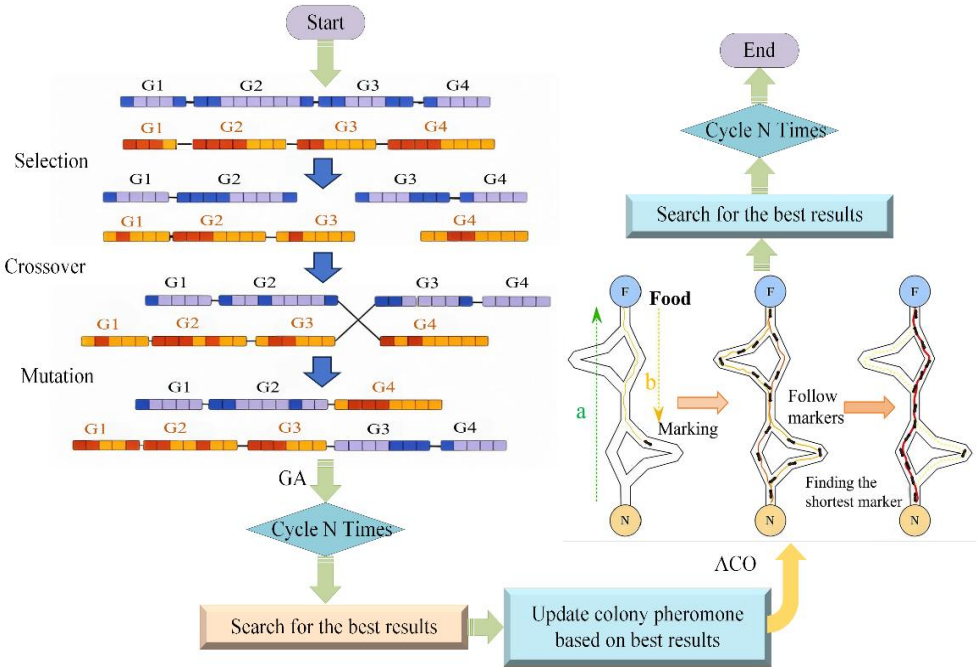
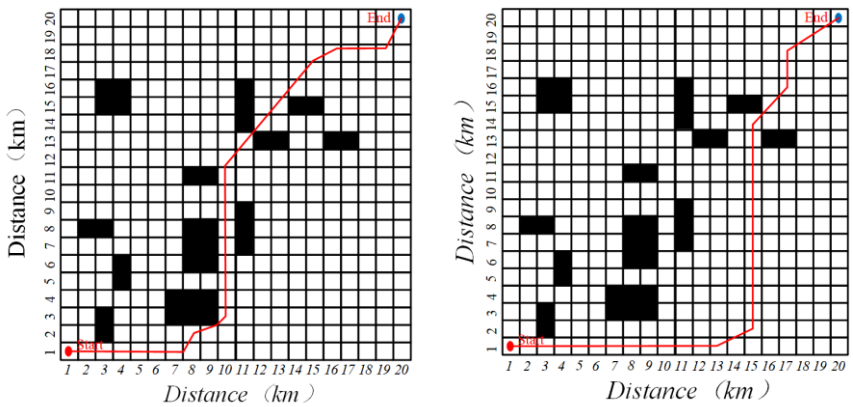


Figure 2: GA-ACO bimodal algorithm flow program diagram

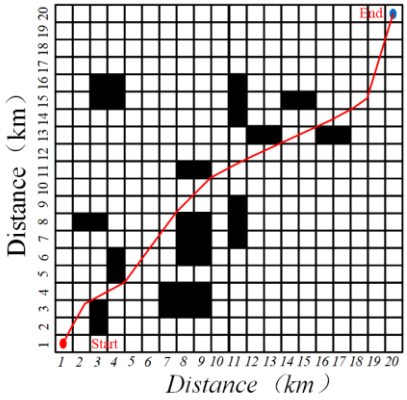
3.3 Experiment and result analysis

To comprehensively evaluate the performance of the algorithm, the experiment compares GA-ACO with advanced algorithms such as the improved ant-lion optimizer, hybrid leapfrog algorithm, and multi-objective gray wolf optimizer. Through comparative analysis, it is concluded that all three algorithms can reach the endpoint from the starting point, but the effective path lengths and running times vary, as shown in Table 1 of the specific iteration results. The data indicates that the optimal path length using the GA-ACO bimodal algorithm is 6% less than that of the ACO algorithm, with an average of 50% fewer iterations, and it has the least number of loops and is the most energy-efficient. Its planned path better meets actual touring needs, verifying the algorithm's effectiveness and superiority in solving multi-constraint path planning problems.

Figure 3 has showed the comparative analysis chart of the three algorithms. Due to the spatiality of the scenic path, the two-dimensionality and three-dimensionality of GA-ACO are simulated and analyzed during the experiment, in which the simulation parameters are shown in Table 2, and the specific experimental results are shown in Figure 4. It is concluded through the experiment that the best path can be obtained in three-dimensional space by using GA-ACO, which proves that GA-ACO can be applied to scenic path planning in three-dimensional space.



(a) Genetic algorithm path trajectories (b) Ant colony optimization path trajectory



(c) Genetic-Ant Colony Bimodal Algorithm Trajectory

Figure 3: Comparative analysis chart of the three algorithms

Table 1: Three algorithmic iterations datasheet

Parameters	Optimal path length	Average path lengths	Average number of iterations	Average number of turns
GA	30.98	31.23	19.45	9.20
ACO	31.78	32.84	27.30	5.40
GA-ACO	29.86	30.92	13.50	3.8

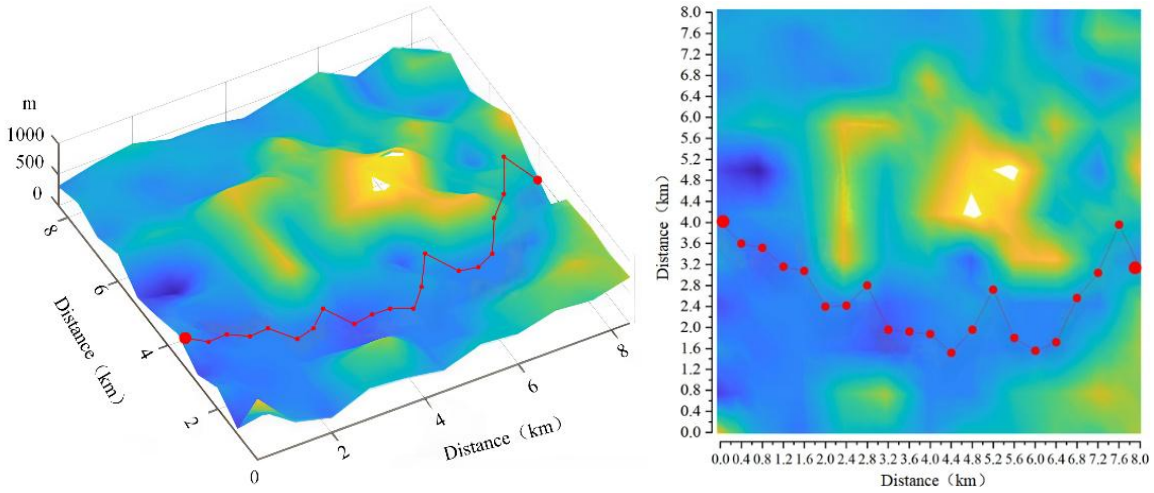


Figure 4: GA-ACO three-dimensional spatial path analysis effect diagram

Table 2: Genetic and ant colony optimization design parameters

Arithmetic	Initial number	Maximum iterations	Relevant parameters
GA	50	400	α=1, β=8, Q =1, $\rho_{initial}$ = 0.9, ρ_{min} = 0.1
ACO	200	150	$a=6$, $b=4$, $c=1$, $P_c=0.78$, $P_m=0.1$, $P_{max}=0.5$

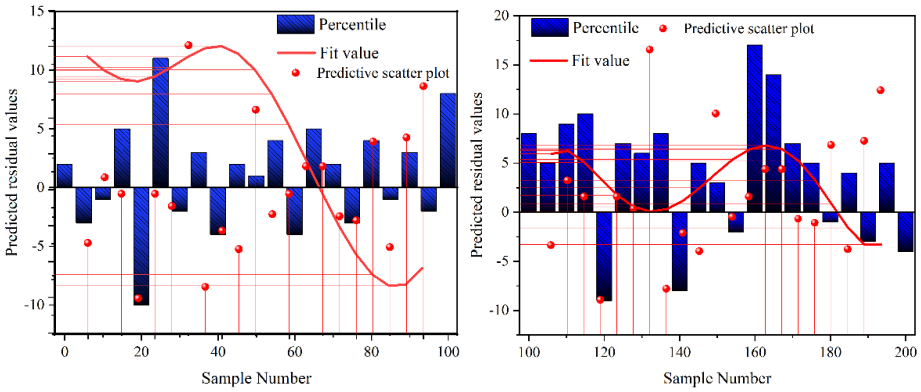


Figure 5: Predictive residual analysis plot for GA-ACO algorithm

Figure 5 shows the performance of the residual values of the GA-ACO predictions, respectively. The left panel shows the residual prediction values at 1-100 predictions and the right panel shows the residual prediction values at 100-200 predictions. It can be concluded from Figure 5 that the mean value of the residuals at 1-100 predictions is smaller than 100-200 predictions, and the maximum of the residuals at 1-200 predictions is 17.3, the minimum is -1.2, and the average absolute residual value is 4.63, which indicates that the gap between the prediction using the algorithm and the actual result is small, and the algorithm has a high degree of credibility in the practical application.

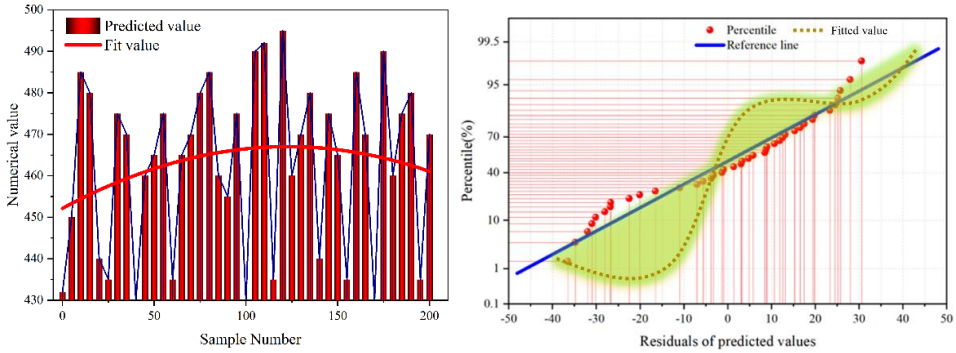


Figure 6: Predicted values of GA-ACO algorithm and predicted residual analysis plots

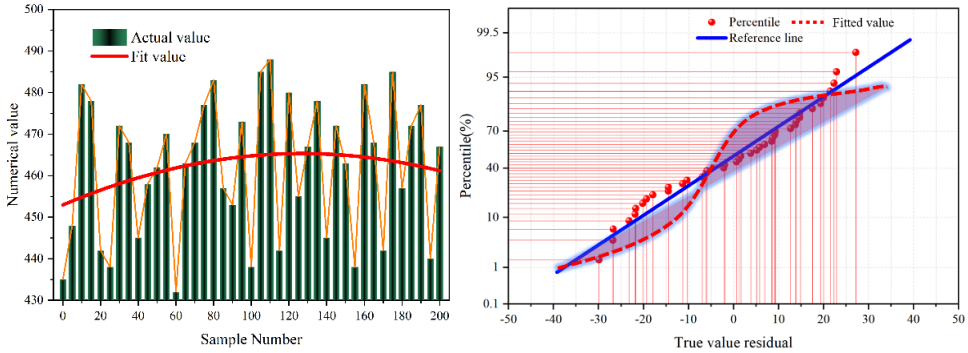


Figure 7: Plot of actual values and actual residual analysis of GA-ACO algorithm

Figure 6 and Figure 7 show the accuracy comparison of the GA-ACO proposed in this paper in the actual smart scenic area path selection, covering the size of the actual value and the predicted value under 200 calculations. It can be concluded from the data in Figure 6 and Figure 7 that there is a certain error between the actual value and the predicted value under each calculation, but the error is controlled within 1%, and the accuracy between the predicted value and the actual value reaches 99.26% after the comprehensive calculation and analysis, which further verifies that GA-ACO has a high degree of reliability in intelligent scenic area path selection

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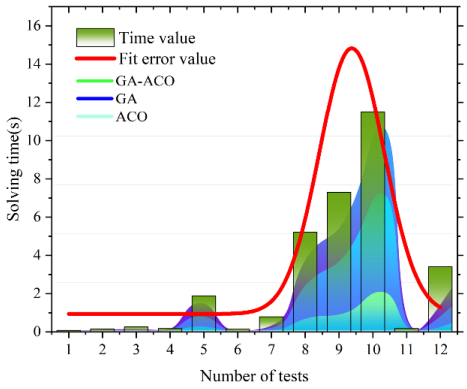


Figure 8: Plot of solving time for the total number of paths for the three algorithms GA-ACO, GA, and ACO

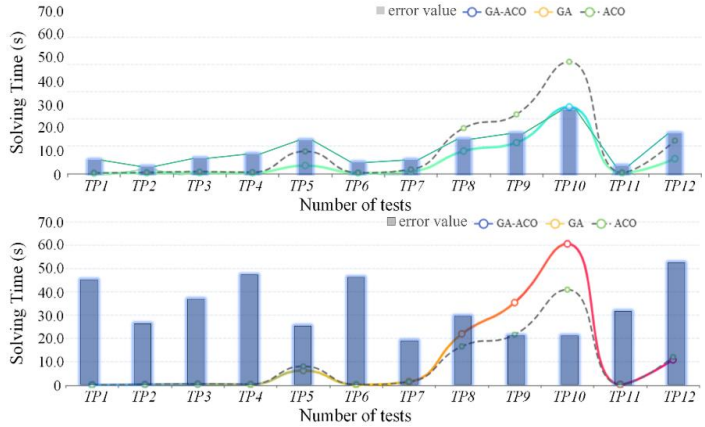


Figure 9: Optimal path solving time graphs for three algorithms GA-ACO, GA, and ACO

Algorithm solution time reflects its responsiveness. To evaluate and compare the optimization performance of the Genetic Algorithm (GA), Ant Colony Optimization (ACO), and the GA-ACO hybrid algorithm (bimodal colony), we recorded the computation time required by each to complete the maximum iterations for two optimization objectives: (1) identifying the total number of feasible paths meeting the requirements, and (2) finding the optimal path. Results are presented in Figures 8 and Figure 9.

Analysis of Figure 8 reveals that the GA-ACO hybrid algorithm exhibited the shortest computation time for identifying the total feasible paths. The largest discrepancy in solution time among the three algorithms occurred at the 10th iteration, reaching a maximum difference of 102.21 s.

Similarly, Figure 9 demonstrates that the GA-ACO hybrid algorithm also achieved the shortest computation time for determining the optimal path. The greatest difference in solution time, observed at the 10th iteration, was 16.2 s.

4 Discussion

This article conducts a sensitivity analysis of key parameters. The results indicate that the pheromone evaporation factor ρ and the pheromone enhancement coefficient Q significantly affect the algorithm's convergence and solution quality: a ρ value that is too high (e.g., ρ>0.8) causes the search to prematurely fall into local optima, while a value that is too low (e.g., ρ<0.3) reduces convergence efficiency; an increase in the Q value can enhance the ability to discover optimal paths, but improvements are limited after exceeding a threshold and increase computational burden. The crossover probability Pc and mutation probability Pm together influence population diversity: when Pc is maintained at 0.6–0.8 and Pm is controlled at 0.05–0.15, the algorithm can maintain a good balance between exploration and exploitation. The number of ants m and the number of iterations T exhibit a synergistic effect: for medium-sized tourist attractions (number of nodes 50–100), m=30–50 and T=100–200 can yield stable and high-quality solutions.

The sensitivity analysis confirms that parameters need to be dynamically adjusted according to the actual scale and complexity of the tourist attraction to balance planning efficiency and robustness.

The experiment aimed to verify the performance of the Genetic Algorithm - Ant Colony Optimization (GA-ACO), selecting standard Genetic Algorithm (GA), standard Ant Colony Algorithm (ACO), and improved Ant Lion Optimization (ALO) as controls. The independent variables included algorithm type, scenic area scene dimension (2D/3D), and visitor preference weights, while the dependent variables were path indicators (length, number of iterations, number of turns), solution time, and prediction accuracy. A digital model was constructed based on a medium-sized smart scenic area layout covering 15 km² with 20 core attractions, with key parameters set (GA population size of 50, crossover probability of 0.75, ACO pheromone heuristic factor of 1.5, evaporation coefficient of 0.5). The computing environment used an Intel Core i7-12700H processor, 32GB DDR4 memory, and Windows 10 system, implementing the algorithm and scene simulation based on Python 3.9 and Matplotlib 3.7. The results were validated through independent sample t-tests (significance level $\alpha=0.05$), showing that the differences in optimal path length (6% shorter than ACO), number of iterations (reduced by 50%), and solution time were statistically significant ($P<0.05$). Moreover, the prediction accuracy in the 3D scene reached 99.26%, and residual analysis further confirmed the reliability of the algorithm.

To further verify the performance of the genetic-ant colony optimization algorithm (GA-ACO), the experiment introduced RRT* (Rapidly-exploring Random Tree algorithm) and PRM (Probabilistic Roadmap algorithm) as benchmarks, comparing them in the same computing environment (Intel Core i7-12700H, 32GB DDR4, Python 3.9) and a medium-sized scenic area model (including real-time congestion and tourist preference constraints). The results show that: in terms of path quality, the optimal path length of GA-ACO (29.86) is 13.5% shorter than RRT* (34.52) and 9.9% shorter than PRM (33.17), with the number of turns (3.8) significantly lower than both (11.6 and 9.3); in terms of efficiency, the optimal path solving time for GA-ACO (18.7s for the 10th iteration) is reduced by 56% compared to RRT* (42.5s) and by 41.4% compared to PRM (31.9s); in terms of dynamic adaptability, when sudden congestion occurs in the scenic area, the re-planning response time of GA-ACO (2.3s) is faster than that of RRT* (5.8s) and PRM (4.1s). An independent sample t-test ($\alpha=0.05$) confirms that the differences are statistically significant ($P<0.05$), further validating the advantages of GA-ACO.

The results of 200 repeated calculations show that its optimal path length (29.86), average number of iterations (13.50), and other metrics are better than those of GA and ACO, with a standard deviation of metrics < 0.5, indicating small performance fluctuations; the prediction error is < 1%, accuracy reaches 99.26%, and the average absolute residual is only 4.63, with residual distribution being concentrated; the solving time is stable, and at the 10th iteration, the time difference with GA and ACO reaches a maximum of 102.21s (total feasible paths) and 16.2s (optimal path), with a coefficient of variation < 0.1; moreover, it can stably generate optimal paths in both two-dimensional and three-dimensional spaces, showing significant robustness and reliability.

5 Conclusion

The GA-ACO proposed in this paper performs well in intelligent scenic area path planning, successfully overcomes the dynamic multi-constraint path planning problem, and provides efficient, accurate and real-time responsive solutions for scenic area path planning, which vigorously promotes the development of intelligent guided tours. The multi-dimensional dynamic adaptive function of GA-ACO can accurately capture the dynamic changes of tourists' preferences and the environment, and integrate the real-time tourists' preferences and the dynamic environmental constraints to achieve a refined path quality assessment. The multi-dimensional dynamic fitness function of GA-ACO can accurately capture the dynamic changes of tourists' preferences and environment, integrate the real-time tourists' preferences and dynamic environment constraints, and realize the refined path quality assessment, which strongly supports the real multi-objective optimization for individuals and scenic spots.

Experimental validation shows that GA-ACO has significant advantages in several key indicators. In terms of path length, compared with the ant colony optimization, the optimal path length of GA-ACO is reduced by 6%; in terms of iteration efficiency, the average number of iterations is reduced by 50%; in terms of turn optimization, GA-ACO has the least number of turns, which effectively improves the smoothness of the paths and energy saving; in the 3D space simulation, GA-ACO can accurately find the optimal paths, which proves its applicability to path planning for scenic spots in 3D space; reliability verification results. In the three-dimensional space simulation, GA-ACO can find the optimal path accurately, which proves that it is suitable for path planning in three-dimensional space in the scenic area; the results of reliability verification show that the algorithm's prediction residuals are small, and the prediction accuracy is as high as 99.26%, which indicates that GA-ACO has a high degree of reliability and trustworthiness in practical application; compared with the traditional algorithms, GA-ACO is shorter in the total number of paths and the optimal path resolution time, which is able to respond to the dynamic changes in the scenic area quickly and provide real-time and efficient

path planning service, which improves the tourists' experience.

Funding

This paper is supported by the Doctoral Research Startup Fund of Weinan Normal University for the project "A Study on the Selection Attributes of Shaanxi Tourism Destinations Based on Tourists' Perception" (No. 501-201122148).

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Survey of Detection Techniques for GPS Spoofing in Connected Vehicles: Taxonomy, Evaluation, and Future Research Directions

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Keywords: connected vehicles, global positioning system spoofing, detection mechanisms, navigation security

Received: June 1, 2025

The Global Positioning System (GPS) plays a pivotal role in modern vehicular systems by providing accurate navigation and timing services. However, its unencrypted and weak signal structure makes it vulnerable to spoofing attacks, especially in connected vehicle environments. This survey comprehensively reviews GPS spoofing detection techniques, categorizing them into five main approaches: signal processing, machine learning (ML), anomaly detection, cryptographic techniques, and sensor fusion. For each category, we analyze the methods' underlying principles, datasets used (e.g., GNSS-SDR, USRP, simulation-based testbeds), and performance metrics including accuracy, precision, recall, and F1 score. The comparative evaluation highlights that hybrid methods and sensor fusion approaches generally offer higher robustness, while ML-based methods achieve high accuracy but require extensive training data. The paper also identifies key challenges, such as a lack of benchmarking standards and performance variability across dynamic environments. Future directions are proposed to address these limitations and improve the reliability and scalability of GPS spoofing detection systems in real-world connected vehicle applications.

Povzetek: Pregled povzema metode za zaznavanje GPS spoofinga v povezanih vozilih ter izpostavi, da so hibridni in fuzijski pristopi najbolj robustni, a manjkajo standardi za primerjavo.

1 Introduction

Advances in communication and transportation technologies have spurred a diverse range of applications that enhance daily life. These advancements encompass robots, virtual reality, and artificial intelligence, transforming how individuals gain information, interact, and travel [1]. Rapid and cost-effective advancement of the high-speed Internet has prompted the development of new services and applications [2] [3]. With the advent of new wireless technologies, new services and applications such as Self-Organized Networks (SONs) and the Internet of Things (IoT) [4], Wireless Sensor Networks (WSN) [5], Vehicular Ad hoc Networks ($VANET$) [6] , and Mobile Ad hoc Network (MANET) [7] has been made possible. GPS technology has been widely adopted across a vast spectrum of applications—spanning military, commercial, and civilian uses—making it an essential tool in modern life. It is also becoming the main timing system and an essential tool for active microwave remote sensing. In addition, GPS is the primary geodetic tool used to monitor crustal deformation in the geophysics community [8].

Smartphones, mobile devices, cars, and Unmanned Aerial Vehicles (UAVs) are equipped with compact GPS receivers for various functions. These services include proposing routes based on predefined requirements, handling an emergency, and providing location-based services. Therefore, to provide consumers with high-quality services, it is imperative to guarantee GPS availability and dependability [9]. GPS spoofing attacks present serious challenges in the context of connected vehicles, as accurate and dependable GPS signals are important for navigation, positioning, and timing [10]. These types of attacks consist of the use of GPS signals by malevolent users to mislead connected vehicles and misdirect their navigation systems [11]. Through broadcasting fake GPS signals that have high power or accurate timing, attackers can provide fabricated location information that leads to incorrect route directions, incorrect estimation of distances, or even collisions [12]. The significance of strong detection tools for GPS spoofing attacks cannot be underestimated. GPS spoofing attack detection and prevention are important to the integrity and security of GPS signals in connected vehicles. Connected vehicles may unknowingly use fabricated or spoofed GPS information without a good detection system in place, which jeopardizes their safety and might result in serious outcomes [13].

To enhance the detection of GPS systems' spoofing attempts, it is important to incorporate various technologies. The accuracy and comprehensiveness in the detection process are enhanced by the IoT capacity to bridge GPS-capable devices and gather real-time information [14] [15]. The capacity of meta-heuristic algorithms to effectively solve complex optimization problems enables GPS spoofing detection algorithms to

perform better [16]. Deep learning (DL) and machine learning (ML) allow systems to learn and adapt, making them capable of differentiating genuine from spoofed GPS signals [17] [18]. Microwave plasma sources play a vital role in the process in that they assist in propagating a controlled environment for the testing and validation of GPS receivers' spoofing resistance [19]. By exposing GPS receivers to spoofing simulation processes, their weaknesses are effectively identified and remedied. Furthermore, urban transportation systems that heavily depend on GPS systems are critical areas for the implementation of a strong spoofing detection mechanism [20]. The vulnerability of public transportation systems to GPS spoofing poses a direct threat to safety and efficiency, necessitating the development of robust detection methods. Therefore, a holistic security approach is indispensable for protecting both the integrity of GPS signals and the safety of all users within today's interconnected vehicular environment. GPS spoofing attack detection also comes with a series of challenging tasks. For example, since fake GPS signals impersonate real GPS signals very well, it is hard for connected vehicles to differentiate between the two. Attackers constantly adapt their techniques, employing sophisticated methods to bypass existing detection systems [6] Another factor to consider is the widespread use of connected vehicles, so successful spoofing attacks can significantly impact multiple vehicles immediately [9]. To effectively tackle these challenges, it is crucial to develop robust detection mechanisms. These systems have to make use of sophisticated signal processing methods, ML algorithms, and anomaly detection strategies to detect and distinguish between real and fake GPS signals precisely. Collaboration between vehicle manufacturers, GPS service providers, and cybersecurity experts is essential [21]. It is possible to improve the detection and mitigation of GPS spoofing attacks by exchanging threat intelligence, developing standardized protocols, and sharing knowledge. For connected cars to remain safe and trustworthy, GPS signals must be secured. Addressing GPS spoofing challenges and implementing robust detection measures will strengthen the resilience of connected vehicles [22] In the context of VANETs, various critical considerations such as QoS and Scalability have been explored to enhance network performance. The security and integrity of GPS data, which are essential for guaranteeing the safe navigation and positioning of connected vehicles, are the main focus of this research, which is unique. This paper presents a comprehensive review of the problems and solutions of GPS spoofing detection in connected vehicles to determine hurdles and outline future directions for research.

In the case of networked vehicles, the increasing security threats posed by GPS spoofing attacks are the motivating force for this endeavor. GPS-based automotive systems have experienced revolutionary advancements as a result of the increasing use of GPS technology in the automotive sector to enhance timing, location, and navigation for both personal and commercial vehicles. Despite the advancements in GPS-based automotive systems, the essentially insecure nature of GPS makes it vulnerable to fraudulent manipulation. With commercial GPS receivers using unencrypted signals that are easily replicable by attackers and the long-distance nature of the transmission of these signals, the vulnerability to GPS spoofing attacks becomes a major problem. In the attack, fake GPS data is inserted into legitimate measurements to falsify vehicles' trajectories and compromise the safety of drivers and pedestrians. The effects of the attack range from incorrect directions to life-threatening collisions, emphasizing the need to create reliable detection mechanisms. The lack of extensive and structured studies in the field of GPS spoofing detection for networked vehicles was the stimulus for this work. Although existing literature discusses various aspects of security in vehicular networks, no holistic analysis of GPS spoofing detection has been conducted. As connected vehicles start to form a part of the transportation system, the reliability and availability of GPS signals are the utmost priority. The present study aims to bridge the gap in the existing research and deliver to the readers a detailed review of current detection approaches, classification of the techniques, as well as a map of the gaps in the areas of research and the directions to proceed. It not only identifies the importance of GPS signal security in connected vehicles but also delivers a strong motivation to the researchers to explore the important area and propose creative solutions to secure the future of the connected vehicular system. In particular, this paper makes the following unique contributions:

- In-depth analysis: The literature is thoroughly reviewed, providing insights into the latest developments and cutting-edge methods in GPS spoofing detection.
- Categorization and comparison: Various detection techniques are categorized and compared, offering a clear framework for understanding the strengths and limitations of each approach.
- This study compares the effectiveness of several GPS spoofing detection techniques using important performance indicators such as Ac, Pr, recall, and $F1$ score. This comparative study sheds important light on the best practices for thwarting GPS spoofing attacks in linked automobiles. By assessing these metrics across different detection techniques, the strengths and weaknesses of each approach are highlighted, aiding in the selection of the most effective strategies.
- Research gaps and future directions: Critical research gaps in GPS spoofing detection for connected vehicles are identified. Highlighting these gaps encourages further exploration and resolution of these challenges in future research.

This is the structure for the remainder of the article. Research methodology is described in Section 2. Section 3 reviews the existing GPS spoofing detection strategies. Section 4 outlines the research gaps and problems, while Section 5 presents the findings.

2 Related works

The study [23] conducts a systematic literature review (SLR) of GPS spoofing attacks, focusing on UAV and GNSS contexts. It categorizes spoofing methods, tools, tests, and techniques, and thoroughly analyzes how various attacks are implemented and detected. The authors also survey existing countermeasures and critically highlight challenges such as the need for real-world validation, the high cost of implementing defenses, and the increasing complexity of attacks and detection algorithms. Their findings provide a structured taxonomy of spoofing strategies and defenses. However, as a survey, it does not introduce new experimental results, and its emphasis on UAVs may limit direct applicability to connected ground vehicles. Its conclusions call for more empirical studies and standardized testing frameworks, aligning with our gap of insufficient real-world validation and benchmarking in spoofing detection.

The work in [24] Presents a comprehensive review of cyberattacks targeting sensors and perception systems in autonomous vehicles. It surveys threats to GPS, LiDAR, cameras, IMUs, and related components, and summarizes machine learning-based defensive techniques. Methodologically, it is a broad narrative review that classifies attacks (including GPS jamming and spoofing) and discusses potential ML defenses to mitigate them. The review highlights how GPS data manipulation can mislead vehicle navigation and underscores general vulnerabilities in autonomy platforms. However, it does not include empirical experiments or propose integrated detection architectures. Its limitations include a lack of new evaluation metrics or real-world testing scenarios; it remains largely descriptive. Thus, while providing useful context on sensor-based attacks, it does not fully address dynamic driving environments or real-time detection frameworks. This gap reinforces the need for practical, validated detection systems that our study aims to explore.

Khan et al. [5] Propose a federated learning (FL) approach for GPS spoofing detection in autonomous vehicles. Using the CARLA driving simulator, each vehicle performs self-localization with onboard sensors (yaw rate, steering angle, wheel speed) and collects both authentic and spoofed trajectories. Local models compute weights from these coordinates, which are then sent to a roadside unit to train a global SVM classifier. FL enables collaborative learning without sharing raw data. The authors report excellent performance (99% accuracy, 98% F1-score) compared to KNN/RF baselines, demonstrating that federated SVM can effectively flag spoofed signals in simulation. However, their method is validated only on simulated CARLA data, not real-world vehicles, and assumes reliable vehicle-to-RSU communication and similar vehicle models. Thus, the approach may not fully capture dynamic traffic conditions or real-world noise, and its practicality under diverse scenarios is untested. This highlights the research gap of limited real-world validation and motivates our work to include live traffic and sensor diversity.

Authors in [13] introduce GPS-IDS, an anomaly-based intrusion detection system for GPS spoofing on autonomous vehicles. The core idea is a physics-based vehicle behavior model: they integrate a GPS navigation model into the conventional dynamic bicycle model to characterize normal AV motion. Temporal features from this model feed into machine learning classifiers that flag deviations as spoofing. They also created the AV-GPS-Dataset (with both real testbed data and CARLA simulations) for evaluation. Results show strong detection: F1 up to 94.4% on real data (with 56.5% faster detection time than a typical EKF-based approach) and 97.1% on simulated urban data. By including real-world experiments, this study directly addresses the validation gap. Its limitations include the controlled nature of the experiments (single vehicle platform, fixed scenarios) and model assumptions (the bicycle model). The generalizability to different vehicle types, multi-vehicle scenarios, or rapidly changing environments is not demonstrated. Such constraints underscore the remaining gap in handling highly dynamic, multi-sensor settings, justifying our focus on broader conditions.

Ying et al. [25] Target GPS spoofing in Connected Vehicle Intersection Movement Assist (IMA) systems. The authors first design an optimization-based attack model that generates realistic spoofed trajectories aimed at triggering false IMA warnings. To defend, they train a one-class classifier (neural network) using only normal vehicle trajectories, enabling detection of unknown spoofing attempts. Using a real-world roundabout dataset, their attack succeeds quickly (<1.7s to trigger IMA), but the detector still identifies anomalies *before* the attack completes. Online detection finds attacks on average 0.49s early, with very low false positive/negative rates. This approach excels in a specific intersection scenario, demonstrating that even aggressive spoofing can be caught. However, it is narrowly scoped: it assumes a fixed roundabout layout and only GPS data, without multi-sensor fusion or adaptation to other road situations. It also relies on offline feature extraction and regular traffic patterns. Its drawbacks include limited generality and no testing under varied traffic or vehicles. These constraints (especially the focus on one scenario) highlight the need for more versatile, scalable detection frameworks, motivating our broader study.

Table 1: Summary of methodology, findings, and limitations of recent GPS spoofing detection studies.

Ref	**Methodology**	**Findings**	**Limitations**
Allão et al. [23]	Systematic literature review of GPS spoofing (UAV focus).	Provides taxonomy of spoofing techniques and defenses; highlights critical needs (e.g., real-world validation).	UAV-centric and survey-only; no new experiments or multi-sensor evaluation; high-level findings with no new data.

Islam et al. [24]	Broad survey of AV sensor and perception attacks (incl. GPS).	Covers numerous attack types and ML-based defenses across sensors; contextualizes GPS spoofing threat.	Descriptive review; lacks empirical analysis or integrated detector design; no real-world benchmarks.
Khan et al.[5]	Federated learning with SVM on CARLA-simulated AV trajectories.	High accuracy (99%) in detecting spoofed trajectories; preserves data privacy by collaborative learning; uses a realistic driving simulator.	Simulation-only (CARLA) experiments; assumes ideal communications and vehicle models; not tested on real traffic.
Abrar et al. [13]	Anomaly detection via physics-based bicycle model (GPS-IDS); new real+sim dataset.	Achieves F1≈94.4% on real data (with faster detection than EKF) and ≈97.1% on simulation; provides first real-world GPS spoofing dataset.	Controlled testbed (single vehicle); may not generalize to other dynamics or multi-vehicle scenarios; relies on model accuracy.
Ying et al. [25]	Optimization-based spoofing attack + one-class neural classifier for IMA.	Can trigger false IMA warning rapidly (<1.7s) and detect it ~0.5s early with very low error; uses only normal data for training.	Focused on one intersection scenario (roundabout); no sensor fusion; assumes consistent traffic behavior; not validated on varied environments.

The reviewed literature, as summarized in Table 1, shows clear advancements in GPS spoofing detection through the use of machine learning, anomaly detection, and federated techniques. High detection accuracies have been reported across several simulated and limited real-world datasets. Review papers contextualize the threat landscape and help establish a taxonomy of countermeasures. However, a consistent limitation across both surveys and empirical studies is the lack of broad real-world validation, diversity in driving environments, and standardized benchmarking protocols. Most existing methods are either scenario-specific, simulation-bound, or assume ideal operating conditions. These gaps, highlighted in both the textual analysis and the comparative evaluation in Table 1, directly motivate the present study, which aims to propose and evaluate a GPS spoofing detection framework designed for scalability, real-time performance, and deployment under varied connected vehicle conditions.

3 Research methodology

This study employed a structured and systematic literature review approach to investigate the current landscape of GPS spoofing detection methods in connected vehicles. To ensure a comprehensive and high-quality synthesis of the relevant research, multiple academic databases were searched, including IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, Wiley Online Library, and Google Scholar. The selection of these databases was based on their relevance and coverage of peer-reviewed publications in the fields of vehicular networks, cybersecurity, and signal processing.

The literature search was conducted using a carefully constructed set of keywords and logical combinations to capture the breadth of research on the subject. These included terms such as “GPS spoofing detection,” “connected vehicles,” “GNSS spoofing mitigation,” “signal processing for GPS spoofing,” “machine learning GPS spoofing,” “sensor fusion GPS security,” and “cryptographic GPS authentication.” The search was restricted to articles published between 2015 and 2024, written in English, and directly related to the detection of GPS spoofing in the context of connected or autonomous vehicles.

To ensure the relevance and quality of the included studies, a set of inclusion and exclusion criteria was applied. Studies were included if they were peer-reviewed journal or conference papers that specifically addressed GPS spoofing detection and employed empirical evaluations, such as simulations or real-world experiments, to report performance metrics, including accuracy, precision, recall, or F1 score. Articles were excluded if they focused solely on GPS jamming rather than spoofing, lacked empirical results, were not published in English, or were duplicates or incomplete in reporting.

After the initial identification and screening process, 78 articles were selected for in-depth analysis. These studies were categorized based on the primary detection approach they employed. Specifically, 17 studies focused on signal processing-based methods, 21 on machine learning techniques, 13 on anomaly detection strategies, 11 on

cryptographic solutions, and 16 on sensor fusion-based methods. This categorization enabled a structured evaluation and comparison of the different technological approaches used in combating GPS spoofing.

From each selected study, key information was systematically extracted, including the study's objectives, detection techniques, spoofing scenarios addressed, types of datasets or testbeds used (such as GNSS-SDR and USRP), and performance evaluation methods. The extracted data were synthesized both quantitatively and qualitatively. Quantitative findings were organized into comparative tables (Tables 7 to 11), which presented performance metrics across different methods. Qualitative synthesis involved thematic analysis to identify recurring patterns, emerging trends, and research gaps.

While early drafts described this synthesis as a "meta-analysis," it is important to clarify that the approach does not involve formal statistical pooling of effect sizes or heterogeneity analysis. Rather, the results presented constitute a descriptive and comparative review of reported outcomes across diverse experimental setups. This methodology offers valuable insights into the state of research in this domain, highlighting the strengths and limitations of various detection techniques and informing future work aimed at enhancing the resilience of GPS systems in connected vehicle environments.

4 *GPS* spoofing attacks: overview and significance

The GPS has ushered in revolutionary opportunities in a range of industries through better navigation, location-based services, and many applications. There exists a very serious concern due to the inherent security vulnerabilities of *GPS* technology, particularly when referring to connected cars. Outside the realm of connected vehicles, *GPS* spoofing attacks pose a very real and dynamic threat to the integrity of *GPS* signals. GPS spoofing attacks include the injection of spoofed GPS data in authentic GPS measurements to provide falsified trajectories and compromise the safety of road users. GPS spoofing has the potential to affect a range of outcomes from rendering incorrect directions to perpetrating potentially devastating accidents. The need to create efficient detection and prevention systems for GPS spoofing cannot be missed. GPS spoofing attacks are marked by their adaptability and versatility through a range of techniques and approaches that represent a real threat to the integrity of GPS signals. Attackers targeting GPS receivers use a variety of methods that challenge the authenticity of the location as well as the timing information received through these receivers.

- Signal retransmission: Signal retransmission is a very common GPS spoofing attack method. In this attack tactic, attackers receive authorized GPS signals and retransmit them, but slightly change them. These changes are made in a way that skews the data received, resulting in incorrect positioning and navigation information. By replicating genuine GPS signals in a slightly changed form, the attackers have the ability to spoof the receiver's perception of its location, which culminates in incorrect directions or even serious safety risks. Signal retransmission poses a significant threat in applications where accurate navigation is critical, for example, in aviation, sea navigation, or autonomous vehicles.
- Signal replay: Another attack technique used by attackers is signal replay. It involves recording real GPS signals in a given location and then replaying the same signals in the future or at some other geographic location. The attackers aim to trick GPS receivers into thinking that these recorded signals are real and up to date. In this way, attackers might mislead GPS receivers to present inaccuracies in location and navigation. For instance, an attacker might first record the GPS signals close to a secure building and later replay the signals close to the building's gate, which might mislead security systems or facilitate unauthorized entry.
- Signal generation: Alternatively, attackers may use the more advanced and more complicated method of signal generation. This method entails creating entirely synthetic GPS signals, often referred to as spoofed signals. These spoofed signals are designed to mimic authentic GPS signals closely. By generating counterfeit signals that imitate the characteristics of genuine ones, attackers can manipulate GPS receivers into accepting and relying on the false location and timing data provided. Signal generation is particularly concerning because it introduces synthetic signals into the GPS ecosystem, potentially leading to multiple receivers unknowingly relying on manipulated data, with serious consequences for navigation and safety.

5 GPS spoofing detection solutions

In order to trick receivers and mislead users, an attacker can modify GPS signals, as seen in Figure 2. The attacker wants to trick unwary users into relying on fictitious position information by manipulating the GPS signals they receive. Specific geographical areas, such as busy intersections or transportation hubs, are targeted to maximize the impact of the deception. By emitting counterfeit GPS signals using specialized equipment, the attacker creates signals that closely resemble genuine ones, tricking GPS receivers into interpreting them as authentic location information. As a result, users unknowingly follow incorrect routes, posing risks such as collisions or individuals getting lost. The spoofed GPS signals can also disrupt other systems reliant on accurate GPS positioning, like autonomous vehicles or emergency services. Detecting GPS spoofing attacks is challenging

due to the similarity between genuine and counterfeit signals, necessitating advanced techniques and specialized equipment for differentiation.

In the preceding section, various GPS spoofing detection techniques were identified. As shown in Figure 3, these techniques can be classified based on underlying principles, including signal processing approaches, ML algorithms, anomaly detection methods, cryptographic techniques, and sensor fusion methods. Each category has its strengths and limitations. Signal processing approaches offer real-time detection capabilities but may be vulnerable to sophisticated spoofing techniques. ML algorithms provide high accuracy but require extensive training data [26]. Anomaly detection methods effectively detect unknown attacks but may produce false positives. Cryptographic techniques enhance signal integrity but may have higher computational requirements. Sensor fusion methods improve detection robustness but may necessitate additional sensor hardware.

5.1 Signal processing approaches

By examining the properties of received GPS signals, several methods are available for identifying GPS spoofing assaults. These methods detect spoofing by monitoring signal strength, time of arrival, and signal consistency. A GPS spoofing detection system depends on the processing of signals for the identification of real as opposed to spoofed signals using the inherent nature of GPS signals. A comparison of the received signals with the expected behavior reveals the spoofing attack. By analysis of the GPS signals received, these algorithms are capable of detecting spoofing efforts and isolating these as opposed to real signals [27]. Signal processing techniques for GPS spoofing detection utilize the following techniques.

- **Signal strength analysis:** Signal strength analysis: It primarily serves to monitor how strong the GPS signals are emanating from satellites. Many spoofing attacks consist of the spoofing of the signal strength so as to deceive the receiver. Discrepancies that signify possible spoofing activity are found through the analysis of discrepancies in the signal strength.
- **Time of Arrival (TOA) Analysis:** GPS signals hold accurate timing data, and spoofing attacks may add delay or modifications to the TOA. Comparing the expected TOA to the observed TOA derived from the received signals using signal processing algorithms depends on the positions of the satellites. Any discrepancy in the expected TOA may signify a spoofing attack.
- **Signal consistency analysis:** GPS signals have consistent patterns in carrier frequency and phase characteristics of the code. Attacks of spoofing will break these patterns, causing irregularity and inconsistency. These irregularities and inconsistencies in patterns are detected by the algorithms for the processing of signals.
- **Multipath analysis:** Multipath results when GPS signals arrive at the receiver along multiple paths, including a direct path and reflected signals. Multipath properties of signals can be spoofed in spoofing attacks. Signal processing algorithms detect spoofing by examining the profiles of the multipath. They detect the anomalies due to spoofing in the multipath profiles.
- **Doppler shift analysis:** Doppler shift occurs as the receiver moves relative to the satellite. Discrepancies in the observed Doppler shift are caused by spoofing attacks. Such discrepancies are identified and marked as possible spoofing events through the use of signal processing algorithms.

Signal processing techniques encompass several algorithms, including cross-correlation, power spectral analysis, statistical analysis, time-frequency analysis, and analysis of the signal-to-noise ratio. These algorithms are contrasted in Table 2 in terms of their strengths and weaknesses. Phase shift and delay caused by a spoofing attack can be detected using cross-correlation-based techniques. Spoofing can be detected by examining temporal anomalies in signals that have already been received. Noise and the interference due to multipath, however, affect the accuracy of cross-correlation computations and render these approaches vulnerable.

In addition to these, there might also be limitations in restraining more advanced spoofing tactics that emulate authentic signal properties. Power spectrum analysis will detect outlying power patterns in GPS signals due to a spoofing attack. It will pick up significant variations in signal properties, including power spikes or plunges. However, the power spectrum analysis might lack the ability to safeguard against advanced spoofing tactics that emulate the power pattern of authentic signals.

Statistical analysis techniques are able to detect changes in statistical patterns in authentic GPS signals. They are capable of observing anomalous signaling behavior that results in spoofing attacks through the examination of diverse statistical parameters. These techniques are vulnerable to changes in the characteristics of the signals due to external conditions and authorized modifications of the signaling. Time-frequency analysis techniques have the ability to view the dynamics and evolution of signals in terms of their changes in time. These techniques have the potential to detect temporal anomalies due to spoofing attacks.

However, it may not always be easy to select the right parameters for the analysis of time-frequency. Time-frequency analysis also has its limitations in the case of intricate changes in a signal. Signal-to-noise ratio analysis examines the extent to which the signals are received. The difference in the quality of signals may help detect counterfeits. An accurate estimation of the noise levels and the signal characteristics is required to analyze signal-

to-noise ratios. It may be susceptible to variations in environmental conditions and noise sources.

In general, signal processing techniques offer insightful information about the properties and actions of GPS signals, making it easier to identify GPS spoofing attempts. Nonetheless, the particulars of the spoofing methods and the required detection precision should be taken into account while selecting a method. Combining different strategies and utilizing complementary methodologies might increase the efficacy of GPS spoofing detection systems. To improve the overall accuracy and resilience of GPS spoofing detection systems, signal processing technologies are frequently integrated with other techniques and provide real-time detection capabilities. Nevertheless, sophisticated spoofing techniques can mimic genuine signals, making their detection more challenging. To fully identify GPS spoofing in connected automobiles, it is crucial to combine signal processing techniques with other techniques like ML and anomaly detection.

5.2 Machine learning approaches

ML algorithms have become powerful tools for detecting GPS spoofing by analyzing large amounts of data and recognizing intricate patterns. By identifying the optimal separation lines, Support Vector Machines (SVMs), which are frequently used for binary classification, have shown they are successful at differentiating between real and fake GPS signals. SVMs excel at finding the most discriminating features that enable the accurate classification of GPS signals. Their ability to handle complex data patterns makes them an essential component of GPS spoofing detection systems, particularly in scenarios where the boundary between authentic and spoofed signals is not easily discernible [28] [29]. On the other hand, random forests perform well in noisy and complex environments, avoiding overfitting and excelling at detecting spoofing attacks. They also provide rankings for the importance of different features, helping identify key indicators of spoofing. Given their capacity to extract pertinent information from unprocessed sensor data and understand intricate correlations, neural networks have become more popular in the field of GPS spoofing detection. They do, however, need a significant quantity of labeled training data to function at their best and appropriate regularization to avoid overfitting [30] [31].

When dealing with huge datasets, the straightforward and easy-to-understand K-Nearest Neighbors (KNN) The approach may become computationally costly. GPS signal properties may be modeled, and anomalies can be found using Gaussian Mixture Models (GMM), which are well-known for their capacity to represent intricate data distributions. However, estimating model parameters can be challenging, and GMM may struggle with high-dimensional data or non-Gaussian distributions [32]. The mentioned algorithms are compared in Table 3. ML algorithms perform well in detecting GPS spoofing, but their accuracy cannot be guaranteed. There are three factors to consider when choosing an algorithm: the application's specific needs, the training data available, and the trade-offs that are desired in performance. The strengths and weaknesses of these algorithms can be combined to develop robust and precise GPS spoofing detection systems. For applications such as connected vehicles, these systems are crucial for maintaining GPS signal integrity and security.

5.3 Anomaly detection approaches

Anomalies in GPS data are detected using anomaly detection techniques. These techniques utilize statistical models or algorithms to determine the patterns of GPS signals and detect discrepancies in these patterns. Anomalies are often discovered using unsupervised approaches like One-Class SVM, GMM, and clustering using K-means. Anomaly detection techniques for GPS spoofing detection detect anomalous patterns or activities in GPS signals that represent spoofing. These techniques use statistical analysis, pattern identification, or data mining to recognize discrepancies in the expected properties of genuine GPS signals. The ability of anomaly detection algorithms to detect slight discrepancies in the properties of GPS signals, even as spoofing techniques improve, is one of their primary strengths. Through the examination of statistical properties of GPS signals, these techniques are able to detect discrepancies that might not be easily detectable by human eyes. Table 4 summarizes anomaly detection techniques for the detection of GPS spoofing.

Clustering algorithms, or a form of anomaly detection technique, amalgamate GPS signals according to their similarities in nature. This method has the advantage of being able to detect clusters of GPS signals that have similar patterns, which may indicate spoofing attacks. Clustering algorithms, however, could have trouble identifying sophisticated and dynamic spoofing strategies. This is because they rely on predefined clusters and may not adapt well to new or unknown attack patterns. On the other hand, pattern recognition methods are another category of anomaly detection techniques. These techniques are intended to detect known patterns or spoofing signatures associated with GPS spoofing. They depend on a complete and updated database of known attack patterns to compare the received GPS signals to these known attack patterns. Pattern recognition techniques can identify known spoofing patterns. Because their performance depends on database quality and availability of existing attack signatures, they might have a hard time identifying new or previously unknown attack patterns. Hybrid techniques that incorporate several techniques, including statistical analysis, pattern recognition, and ML, are robust in GPS Spoofing detection. The precision and robustness of GPS Spoofing systems can be enhanced through the use of hybrid techniques that harness the strengths of different detection techniques while suppressing their weaknesses. However, developing and tuning hybrid techniques might need extra computational power and skills.

5.4 Cryptographic approaches

Cryptography-based techniques are very effective in the detection of GPS spoofing in connected vehicle systems. Cryptography algorithms and protocols are utilized in the techniques to limit the vulnerability to spoofing attacks and ensure the validity and integrity of GPS signals. A tabular description of the use of cryptography-based techniques in GPS spoofing detection appears in Table 5. With the use of encryption algorithms, cryptography-based techniques provide robust security measures that hinder the ability of attackers to spoof GPS signals without being noticed. By asserting the authenticity of GPS signals, authentication techniques such as digital signatures and certifications guard against man-in-the-middle and replay attacks. These techniques secure the system as a whole. The successful use of cryptographic techniques lies in the secure application of key management procedures. The performance and reliability of cryptography-based techniques are guaranteed by secure key management that ensures confidentiality and integrity of cryptographic keys to avoid tampering or unauthorized use. In summary, cryptography-based techniques provide robust security and authentication functions for GPS spoofing detection. They are a strong countermeasure against spoofing attacks. However, the efficiency of the practical application of cryptography techniques must be considered in terms of factors such as computational complexity and secure management of the key.

5.5 Sensor fusion approaches

Through the integration of data gathered by several sensors, including GPS, accelerometers, gyroscopes, and magnetometers, sensor fusion methods detect GPS spoofing. Inconsistencies among different readings, which might indicate a spoofing attack, may be discovered through the use of data from various sensors. For instance, in case a GPS receiver delivers a location that differs in a way that does not match the readings obtained by the accelerometer, gyroscope, or magnetometer, it is most probable that a spoofing attack is in process. Beyond fusing data from inertial sensors, another robust approach is to integrate GPS data with information from vision sensors. Advanced computer vision techniques, such as methods for real-time visual target tracking in aerial videos, can provide an independent source of motion and position verification, making the system more resilient to spoofing attacks [33]. The sensor fusion methods for the detection of GPS spoofing are presented in Table 6. The sensor fusion techniques are useful in reducing the limitations and weaknesses of single sensors. They use data gathered by multiple sensors to counter sensor inaccuracies, environmental interference, and signal tampering.

Furthermore, since an attacker would need to concurrently alter many sensor signals in order to fool the system, sensor fusion strengthens GPS systems' resistance to spoofing attacks. However, these methods pose certain challenges as well. A reliable fusion requires careful calibration and synchronization of sensor data. The accuracy of fusion results can be affected by sensor noise and bias. Additionally, sensor fusion methods may require adequate computational resources.

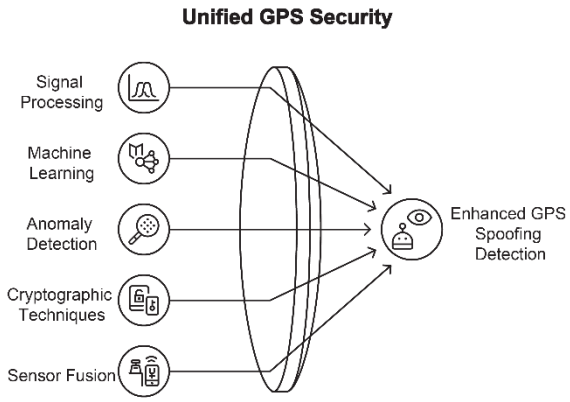


Figure 1: Taxonomy of GPS spoofing detection techniques for connected vehicles, categorized by methodological foundations and subtypes. The structure highlights overlap, dependencies, and hybridization opportunities across the detection landscape.

To provide a structured overview of the GPS spoofing detection landscape, Figure 1 presents a taxonomy of detection techniques based on their core methodological principles. The classification divides existing approaches into five major categories: signal processing, machine learning, anomaly detection, cryptographic techniques, and sensor fusion. Each category is further subdivided based on detection strategy or implementation model, highlighting overlaps and potential hybridization opportunities. This taxonomy serves as a conceptual map for understanding the relationships, strengths, and limitations of the various approaches discussed throughout the survey.

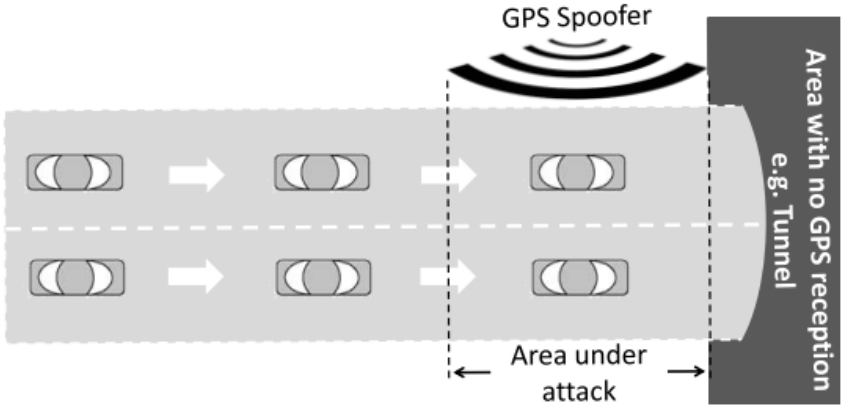


Figure 2: GPS spoofing attack scenario [32].

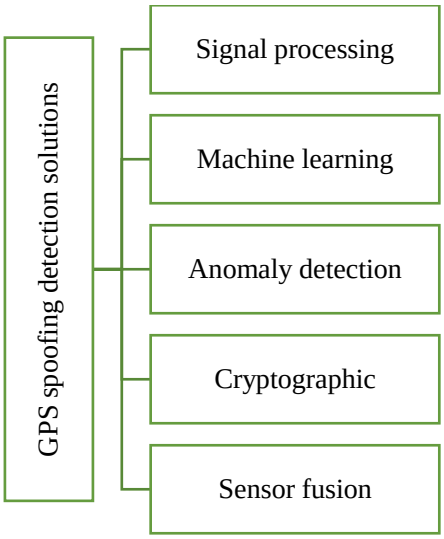


Figure 3: Taxonomy of detecting *GPS* Spoofing solutions.

Table 2: An analysis of several signal processing techniques for detecting *GPS* Spoofing.

Approach	Key idea	Dataset	Attack detection algorithm	Performance measures	Weaknesses	References
Cross-correlation	Effective in detecting signal delay and phase discrepancies	N/A	Cross-correlation calculations	Temporal inconsistencies	Susceptible to noise and multipath interference Limited effectiveness against sophisticated spoofing techniques	[34] [35] [36] [37] [38] [39] [40] [41] [42]
Power spectrum analysis	Able to identify abnormal power distribution in GPS signals	N/A	Power spectrum analysis	Major changes in signal characteristics	Limited effectiveness against sophisticated spoofing techniques	[43] [44] [45]
Statistical analysis	Can detect deviations from statistical patterns	N/A	Statistical metrics analysis	Abnormal signal behavior	Vulnerable to variations in signal characteristics	[9] [46]

	exhibited by genuine GPS signals				due to environmental factors and legitimate signal modifications	
Time-frequency analysis	Provides insights into the dynamics and changes of signals over time Detects temporal inconsistencies caused by spoofing	N/A	Time-frequency analysis	Temporal inconsistencies	Challenging to determine the appropriate parameters Limited effectiveness in scenarios with complex signal variations	[47] [48]
Signal-to-noise ratio	Focuses on the quality of received signals Can detect discrepancies in signal quality between genuine and spoofed signals	N/A	Signal-to-noise ratio analysis	Signal quality discrepancies	Requires accurate estimation of noise levels and signal characteristics Susceptible to variations in environmental conditions and noise sources	[49] [50] [51]

Table 3: A comparison of ML approaches for GPS spoofing detection.

Approach	Key idea	Dataset	Attack detection algorithm	Performance measures	Weaknesses	References
Support vector machines	Effective in separating genuine and spoofed GPS signals	Labeled training data	SVM classification	Accuracy and false positive rate	Performance may degrade with large datasets	[52] [53] [54] [55]
Random forests	Robust against noise and overfitting	Labeled training data	Random forest classification	Accuracy and feature importance	Computationally expensive for large datasets	[56] [57] [58] [59]
Neural networks	Able to learn complex nonlinear relationships	Labeled training data	Neural network classification	Accuracy and training data size	Require a large amount of labeled training data	[60] [61] [62] [63] [64] [65] [66]
K-nearest neighbors	Simple and intuitive algorithm	Labeled training data	KNN classification	Accuracy and computational efficiency	Computationally expensive for large datasets	[67] [68]
Gaussian mixture models	Suitable for modeling complex data distributions	Labeled training data	GMM classification	Accuracy and model parameters	Estimation of model parameters can be challenging	[69] [70]

Table 4: A comparison of anomaly detection methods for GPS spoofing detection.

Approach	Key idea	Dataset	Attack detection algorithm	Performance measures	Weaknesses	References
Statistical analysis	Able to detect subtle deviations in GPS signals	N/A	Statistical analysis	Anomalies in signal attributes	May struggle with complex and evolving spoofing techniques	[71] [72]

					Requires well-defined statistical models and thresholds	
Clustering	Can identify clusters of similar GPS signal patterns Potential to detect new attack patterns	N/A	Clustering algorithms	Detection of spoofing clusters	May struggle with complex and evolving spoofing techniques Dependence on predefined clusters Difficulty in adapting to novel attack patterns	[73] [74]
Pattern recognition	Effective in detecting known spoofing techniques Utilizes a comprehensive attack signature database	Attack signature DB	Pattern recognition methods	Match with known attack patterns	Difficulty in identifying new or previously unseen attack patterns Dependence on accurate and up-to-date attack signatures	[75] [76]
Hybrid	Combines the strengths of multiple detection methods Enhances accuracy and robustness	N/A	Hybrid methods	Enhanced accuracy and robustness	Requires additional computational resources and expertise for implementation and fine-tuning	[77] [78]

Table 5: A comparison of cryptographic methods for GPS spoofing detection.

Approach	Key idea	Dataset	Attack detection algorithm	Performance measures	Weaknesses	References
Encryption	Provides strong security for GPS data Prevents unauthorized access and tampering	N/A	Encryption algorithms	Signal integrity and data confidentiality	Introduces computational overhead Increased latency or delay in processing	[79] [80] [81]
Authentication	Verifies the authenticity of GPS signals	N/A	Digital signatures and certificates	Signal integrity and protection from replay and MITM attacks	Requires secure key management practices	[81] [82] [83] [84]
Digital signatures	Protects against replay and man-in-the-middle attacks	N/A	Digital signatures and certificates	Signal integrity and protection from replay and MITM attacks	Key confidentiality and integrity must be maintained	[85] [86]

Table 6: A comparison of GPS spoofing detection techniques using sensor fusion.

Approach	Key idea	Dataset	Attack detection algorithm	Performance measures	Weaknesses	References
Integration of GPS data with other sensors	Complementary information from multiple sensors improves accuracy and reliability. Enables detection of	Sensor data	Sensor fusion techniques	Detection of inconsistencies between GPS and other sensors	Requires calibration and synchronization of sensor data Higher computational complexity compared to	[87] [88] [89]

	inconsistencies between GPS data and data from other sensors				other detection techniques	
Fusion of accelerometer and magnetometer data	Provides additional information about vehicle movement and orientation Can detect deviations and inconsistencies indicating GPS spoofing	Sensor data	Sensor fusion techniques	Detection of GPS inconsistencies and accelerometer/magnetometer data	Requires accurate calibration and synchronization of sensor data Vulnerable to sensor noise and biases.	[90] [91]
Fusion of GPS data with gyroscopic data	Enhances detection capabilities by incorporating rotational information Can detect discrepancies between GPS data and gyroscopic measurements	Sensor data	Sensor fusion techniques	Detection of discrepancies between GPS data and gyroscope data	Requires accurate calibration and synchronization of sensor data Vulnerable to gyroscopic sensor errors.	[92]
Fusion of GPS data with barometric data	Provides altitude information for additional context Can identify inconsistencies between GPS altitude and barometric readings	Sensor data	Sensor fusion techniques	Detection of inconsistencies between GPS altitude and barometric readings	Requires accurate calibration and synchronization of sensor data Susceptible to errors due to changing environmental conditions	[88] [89] [90] [91] [92] [93]

6 Performance comparison

The following section outlines a performance evaluation of various signal-processing techniques employed for GPS spoofing attack detection. For each method, typical performance parameters such as sensitivity, specificity, false positive rate, and the accuracy of detection are evaluated. Through an examination of these parameters, the performance of each approach in identifying legitimate GPS signals and spoofed signals can be contrasted. Through this analysis of the merits and demerits of various approaches, the study provides information on the performance of these approaches in practice.

6.1 Signal processing-based methods

Data obtained from published papers are utilized to demonstrate the results of the performance of techniques based on signal processing to provide a comprehensive analysis of the performance. Performance results of different approaches are contrasted. Among the techniques reviewed are the PCA-CNN-LSTM Model, SVM, commercial receiver metrics, DL-based Method, Improved SQM Moving Variance, and SQM. The ability of these methods to detect GPS spoofing efforts is comprehensively tested using standard performance measures such as Ac, Pr, $recall$, and $F1$ score. It becomes simpler to select the most effective approach for real-world use when approaches are compared because it provides insightful information about their merits and limitations.

Table 7: Performance results of signal processing-based methods.

Method	***Accuracy***	***Precision***	***Recall***	***F1 Score***
PCA-CNN-*LSTM* Model	99.49%	97.98%	96.50%	97.22%
SVM	98.50%	98%	99%	98.50%
Metrics from Commercial Receivers	96%	95%	97%	96%
Improved SQM Moving Variance	97.20%	96.80%	97.60%	97.20%
SQM	95.50%	95%	96%	95.50%
DL-based method	94.70%	93.90%	95.50%	94.70%

As indicated in Table 7, the efficiency results of the signal processing-based approaches for spoofing attempt identification vary in their efficacy across the techniques. With 99.49% Ac, 97.98% Pr, 96.50% $recall$, and a 97.22% $F1\ score$, the PCA-CNN-LSTM Model performs best overall as it exhibits the highest resistance to the detection of spoof signals while minimizing the occurrence of both false positives and negatives. The SVM approach also performs very strongly with a significant Ac of 98.50% and a very high recall rate of 99%, and it is very effective in the detection of spoofed signals, but sometimes misclassifies real signals. Metrics from commercial receivers and the Improved SQM Moving Variance method show moderate performance, with accuracies of 96% and 97.20%, respectively, suggesting they are reliable but not as consistent as the top performers. The SQM method and the DL-based method are the least effective, with the latter showing the lowest performance at 94.70% Ac, indicating challenges in reliability and higher rates of false classifications. Overall, the analysis highlights the PCA-CNN-LSTM Model as the superior method due to its high detection capabilities, while the DL-based method is the least effective, emphasizing the need for careful selection of detection methods based on specific requirements and spoofing attack characteristics.

6.2 ML-based methods

Based on the data collected from published research articles, this section illustrates the performance results of ML-based approaches for GPS spoofing attempt identification. The methods compared include SVM, C-SVM, Nu-SVM, ANN Technique, PNN, DT, Random Forest, Gradient Boosting, and AdaBoost. $F1$ score, $recall$, Ac, and Pr are the performance parameters that are utilized for comparison.

Table 8: Performance results of ML-based methods.

Method	Accuracy (Ac)	Precision (Pr)	Recall	F1 Score
SVM, C-SVM, Nu-SVM	98.70%	98.20%	99.10%	98.60%
ANN Technique	97.30%	96.70%	97.90%	97.30%
PNN, DT	96.50%	96%	97%	96.70%
Random Forest	98.30%	97.90%	98.70%	98.30%
Gradient Boosting	97.60%	97.10%	98.10%	97.60%
AdaBoost	96.20%	95.70%	96.70%	96.20%

In terms of Ac, Pr, $recall$, and $F1$ score, Table 8 shows the performance outcomes of many ML-based techniques for identifying GPS spoofing attempts. Among the methods evaluated, SVMs, including C-SVM and Nu-SVM variants, demonstrate superior performance with an Ac of 98.70%, Pr of 98.20%, $recall$ of 99.10%, and $F1$ score of 98.60%. SVMs are well-known for their efficiency in binary classification problems, and they seem to show exceptional accuracy and robustness in differentiating between real and fake GPS signals. On the other end of the spectrum, AdaBoost shows the lowest performance metrics among the methods listed, achieving an Ac of 96.20%, Pr of 95.70%, $recall$ of 96.70%, and $F1$ score of 96.20%. While still achieving respectable metrics, AdaBoost performs slightly lower compared to SVMs, indicating it may struggle more with the nuanced characteristics of GPS spoofing attacks or could be more susceptible to noise and variability in signal data. Overall, SVM variants emerge as the top performers in this comparative analysis, suggesting their suitability for robust and accurate GPS spoofing detection systems, while AdaBoost, though effective, may benefit from additional refinements or complementary techniques to enhance its performance further.

6.3 Anomaly detection-based approaches

This part covers the performance results of anomaly detection-based techniques for GPS spoofing attack detection. The obtained results are gathered through published papers and contrasted for different techniques, which include GPS-IDS, One-Class SVM, Multicorrelator Distortion Monitoring, Ensemble Models (Bagging, Stacking, Boosting), and KNN.

Table 9: Performance results of anomaly detection approaches.

Method	Accuracy	Precision	Recall	F1 Score
GPS-IDS	98.70%	98.30%	99.10%	98.70%
One-Class SVM	97.50%	97%	98%	97.50%
Multicorrelator Distortion Monitoring	96.80%	96.40%	97.20%	96.80%
Ensemble Models (Bagging, Stacking, Boosting)	95.60%	95.10%	96.10%	95.60%
K-nearest Neighbors (KNN)	94.70%	94.20%	95.20%	94.70%

Based on the values collected for Ac, Pr, $recall$, and $F1$ score, the performance results of most anomaly detection algorithms used to detect GPS spoofing attacks are presented in Table 9. Among the algorithms tested, GPS-IDS ranks as the top-performing system with 98.70% Ac, 98.30% Pr, 99.10% $recall$, and an $F1\ score$ of 98.70%. These values indicate how effectively GPS-IDS discriminates between anomalous and regular activities and its strong ability to detect real as well as counterfeit GPS signals. In contrast, the algorithm that has relatively low performance values in all classes is the KNN algorithm, which has an Ac of 94.70%, Pr of 94.20%, $recall$ of 95.20%, and an $F1$ score of 94.70%. Although the algorithm's performance is relatively lower than that of GPS-IDS, it still performs successfully. This implies that there is a high chance of wrongly flagging real signals as fake or vice versa. Overall values indicate the importance of using anomaly detection algorithms that are well-suited to the distinctive nuances and complexity of GPS spoofing detection contexts to provide the maximum accuracy and reliability while defending GPS systems against hostile attacks.

6.4 Cryptographic-based approaches

This section highlights the performance results of the cryptography-based approaches for GPS spoofing detection, compiled through information gathered in publications. The outcomes for these different approaches, namely Dynamic Selection Techniques, Blockchain Integrated Framework, Quantum Cryptography, and LSTM Algorithms, have been cross-compared.

Table 10: Performance results of cryptographic-based approaches.

Method	Accuracy	Precision	Recall	F1 Score
Dynamic Selection Techniques	99.60%	98.40%	98.90%	98.60%
Blockchain Integrated Framework	95%	94%	96%	95%
Quantum Cryptography	96%	95%	97%	96%
LSTM Algorithms	97%	96%	98%	97%

Performance outcomes of cryptographic-based approaches to GPS spoofing attack identification are presented in Table 10 and include the Ac, Pr, $recall$, and $F1$ score for each approach. Dynamic Selection Techniques stand out as the top-performing approach in all the above values based on 99.60% Ac, 98.40% Pr, 98.90% $recall$, and an $F1\ score$ of 98.60%. The technique performs exceptionally well in the identification of both authentic GPS signals and spoof ones, and therefore emerges as the best approach among the approaches given. Second in performance comes the Blockchain Integrated Framework that also performs well with 95% Ac, 94% Pr, 96% $recall$, and a corresponding $F1$ score of 95%. Although slightly lower in performance in comparison to Dynamic Selection Techniques, the Blockchain Integrated Framework still cuts through very effectively. Quantum Cryptography and LSTM Algorithms have slightly lower but commendable performance values whereby Quantum Cryptography attains a performance of 96% Ac, 95% Pr, 97% $recall$, and an $F1$ score of 96%, and $LSTM$ Algorithms attains a performance of 97% Ac, 96% Pr, 98% $recall$, and an $F1$ score of 97%. These approaches, even though not the highest performing in this review, still have effective detection and serve to demonstrate their potential for GPS signals to guard against spoofing attacks. Overall, Dynamic Selection Techniques stand out as the most effective method in this study, while all listed cryptographic-based approaches showcase strong potential in enhancing GPS spoofing detection systems.

6.5 Sensor fusion-based approaches

Performance results of sensor fusion-based methods are presented based on data collected from published research papers, and their results are compared for these methods. Inertial sensor-based location shifts, KNN combined with Dynamic Time Warping (DTW), steering angle sensor-based turn detection, GNSS and inertial sensor fusion, LSTM networks for predicted location shifts, and vehicle motion state monitoring are just a few of the sensor fusion techniques whose performance is summarized in Table 6. Similar to this, the comparison highlights the efficacy of each method in identifying GPS spoofing assaults by including important performance measures, including Ac, Pr, $recall$, and $F1\ score$.

Table 11: Performance outcomes of sensor fusion-based approaches.

Method	***Accuracy***	***Precision***	***Recall***	***F1 Score***
LSTM Network for Predicted Location Shift	98.50%	98%	99%	98.50%
KNN and DTW	97.80%	97.30%	98.30%	97.80%
Inertial Sensor-Based Location Shift	96.70%	96.20%	97.20%	96.70%
Speedometer and Accelerometer Fusion	95.50%	95%	96%	95.50%
Steering Angle Sensor-Based Turn Detection	94.90%	94.40%	95.40%	94.90%
GNSS and Inertial Sensor Fusion	93.60%	93.10%	94.10%	93.60%
Vehicle Motion State Monitoring1	92.70%	92.20%	93.20%	92.70%

Finally, the performance results of most sensor fusion-based solutions for detecting *GPS* spoofing attempts are presented in Table 11. Ac, Pr, *recall*, and $F1\ score$ are the four key measures to compare each solution. With an Ac of 98.50%, Pr of 98%, *recall* of 99%, and $F1\ score$ of 98.50%, the LSTM network for predicted location shift easily tops the list of the ones discussed. This approach illustrates a high robustness in predicting and detecting location changes due to spoofing using the temporal dependencies captured in LSTM networks. Second in line comes the KNN along with DTW, having high values in all measures with 97.80% accuracy (Ac), 97.30% Pr, 98.30% *recall*, and a corresponding $F1\ score$ of 97.80%. These findings demonstrate how well distance-based techniques work in conjunction with time series similarity metrics to identify fake GPS signals. On the other end of the spectrum, while all methods demonstrate strong performance, vehicle motion state monitoring shows slightly lower metrics with 92.70% Ac, 92.20% Pr, 93.20% *recall*, and an $F1\ score$ of 92.70%. While effective, this method exhibits relatively lower performance than the LSTM and KNN/DTW approaches, possibly due to its reliance on less complex sensor fusion techniques. Overall, the table shows how effective advanced sensor fusion techniques such as LSTM networks and complex distance-based algorithms are at improving the precision and dependability of *GPS* spoofing detection systems. It also offers information about the advantages and disadvantages of each technique for practical use. Correspondingly, visual representations of performance comparison for different approaches are shown in the Figures. 4 to 8.

The performance metrics presented in Tables 7 through 11 are extracted directly from peer-reviewed publications selected during the systematic literature review. These results were not re-implemented or reproduced experimentally in this study. Instead, the reported accuracy, precision, recall, and F1 score values were collected as published in the original papers. When available, values were taken from comparative evaluation sections or experimental result summaries within each study. In cases where multiple configurations were tested, the most representative or highest-performing result was selected for inclusion. Although the data offers valuable comparative insight, it is important to note that variations in experimental setup, dataset characteristics, and evaluation conditions across studies may affect direct comparability. As such, the tables provide a descriptive aggregation of reported results rather than a normalized or statistically pooled meta-analysis.

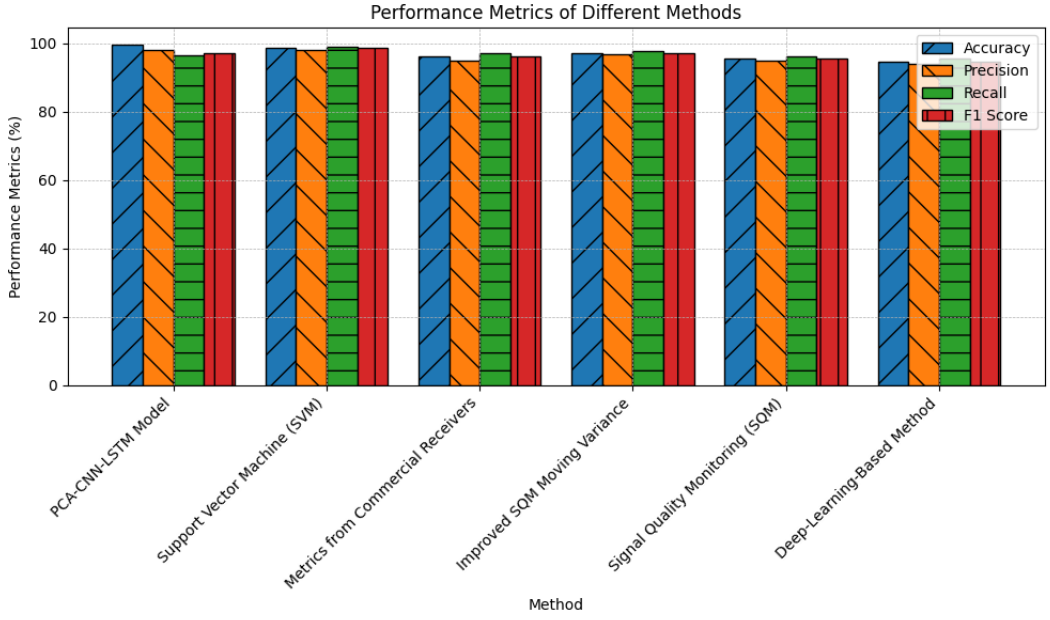


Figure 4: Performance comparison of signal processing-based GPS spoofing detection methods based on accuracy, precision, recall, and F1 score.

Figure 4 presents a comparative visualization of the performance of signal processing-based methods for detecting GPS spoofing attacks. Among these, the PCA-CNN-LSTM model demonstrates superior detection capability with the highest accuracy, precision, and F1 score, highlighting its ability to model complex signal characteristics. In contrast, the DL-based method shows comparatively lower performance, suggesting its sensitivity to signal variability or overfitting in certain environments. This figure illustrates the trade-off between traditional statistical models and newer deep learning approaches in signal processing domains.

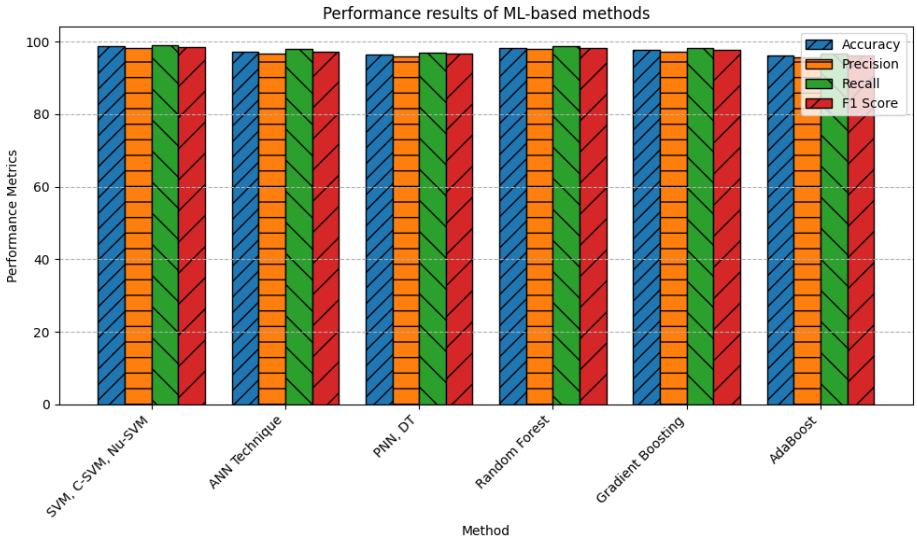


Figure 5: Evaluation of machine learning-based GPS spoofing detection methods, highlighting classification performance across standard metrics.

Figure 5 illustrates the performance comparison of machine learning-based detection methods. SVM and Random Forest models consistently outperform others in terms of accuracy and recall, reflecting their strength in handling high-dimensional signal data. AdaBoost, although effective, trails slightly behind, possibly due to its sensitivity to noise or imbalanced datasets. The figure emphasizes the importance of model selection and data quality in ML-based spoofing detection systems.

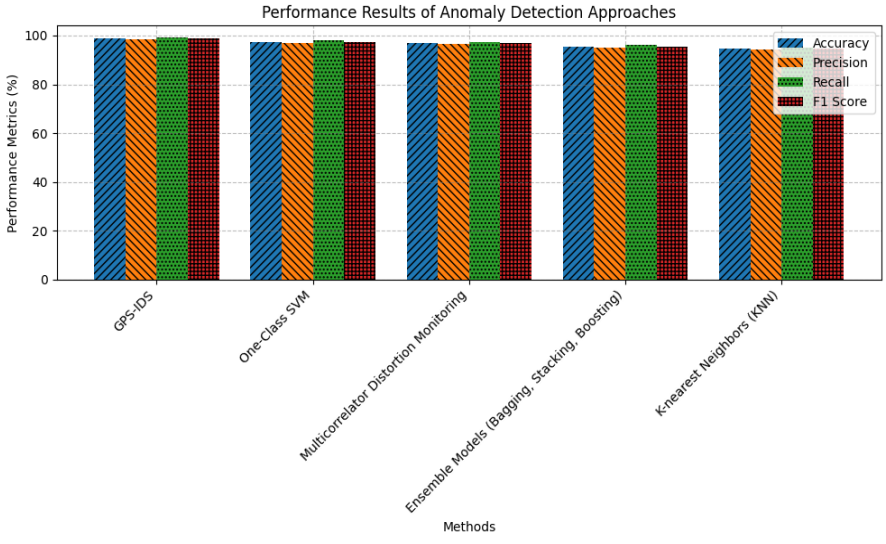


Figure 6: Comparative performance of anomaly detection techniques for identifying GPS spoofing patterns in real or simulated environments.

Figure 6 shows the performance of anomaly detection approaches. GPS-IDS achieves the highest metrics across all evaluated parameters, followed closely by One-Class SVM. Ensemble models and KNN-based methods show slightly lower performance, indicating that while anomaly detection is effective at identifying unknown spoofing patterns, its precision may suffer in complex or noisy environments. This figure supports the use of hybrid anomaly detection models that balance flexibility with precision.

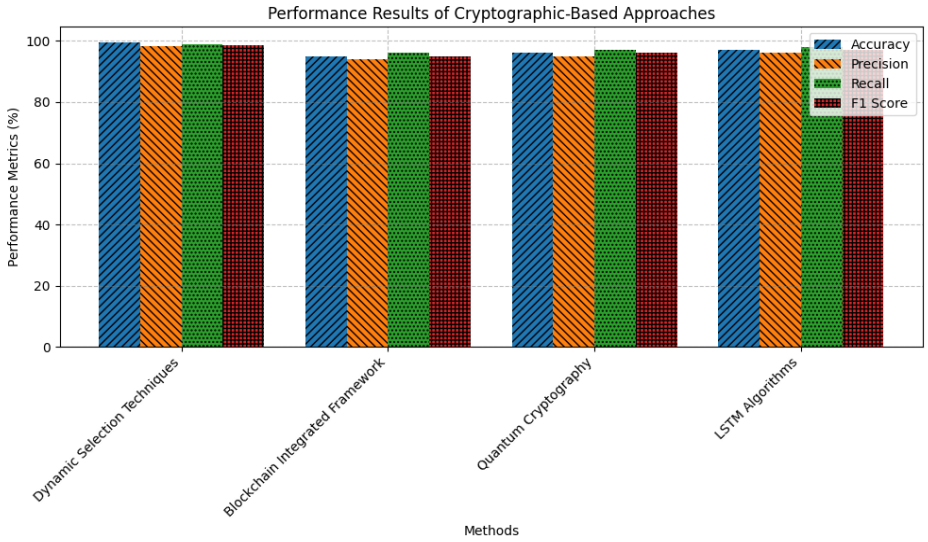


Figure 7: Comparison of cryptographic-based spoofing detection approaches emphasizing signal integrity and resistance to manipulation.

Figure 7 compares cryptographic-based techniques. Dynamic Selection Techniques lead the category with near-perfect scores across all metrics, showing strong potential for secure signal validation. Blockchain and quantum cryptography approaches also perform well, but are slightly constrained by implementation complexity. This visualization reinforces the robustness of cryptographic solutions for secure environments, though real-time feasibility remains a concern.

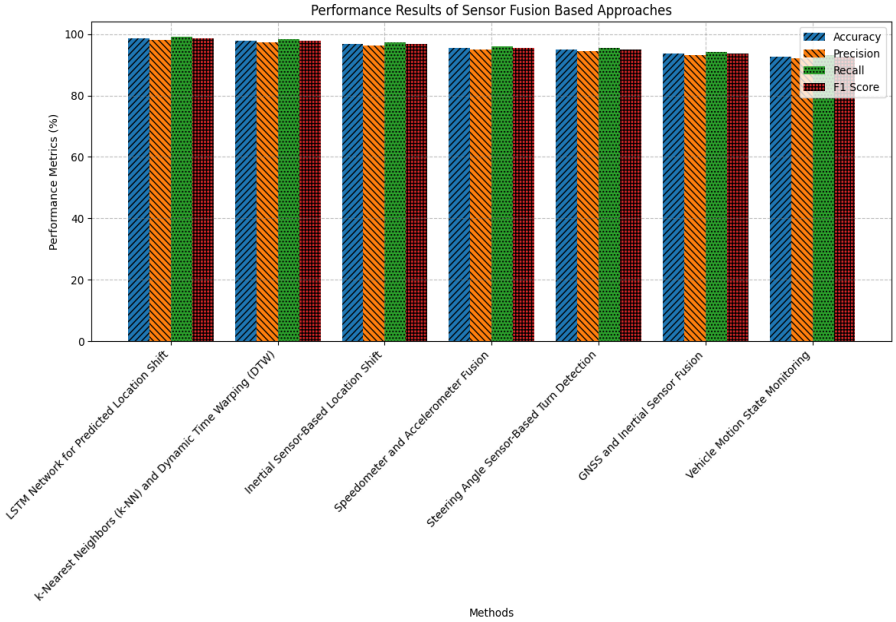


Figure 8: Performance of sensor fusion methods using data from GPS, IMUs, and other onboard sensors to detect spoofing attacks.

Figure 8 presents sensor fusion-based techniques, with the LSTM network for predicted location shift emerging as the most accurate method. KNN with DTW also performs strongly, particularly in detecting spoofed trajectories through temporal alignment. Methods like vehicle motion state monitoring exhibit lower scores, potentially due to limited context or less precise data fusion. The figure clearly illustrates that integrating diverse sensor inputs significantly enhances detection robustness, though it may introduce synchronization and hardware challenges.

7 Discussion

The comparative performance results presented in Tables 7 through 11 and visualized in Figures 4 to 8 reveal several important trends across GPS spoofing detection techniques. Rather than treating these categories in isolation, this section examines how these methods perform under varying technical demands, environmental conditions, and implementation constraints. It also highlights the trade-offs between detection accuracy, robustness, computational efficiency, and deployability in real-world connected vehicle systems.

Among all techniques, signal processing-based methods demonstrate consistently high performance in controlled settings, particularly models that integrate advanced signal representation techniques such as PCA-CNN-LSTM. These methods benefit from their capacity to detect low-level physical signal anomalies, making them suitable for real-time deployment. However, their effectiveness tends to degrade in dynamic, urban, or noisy environments were spoofed signals closely mimic legitimate ones. While methods like SVM and moving variance SQM offer near 98% accuracy, they are often tested in simulation or lab-controlled environments, raising questions about their generalizability and resilience under GPS multipath interference or satellite visibility loss.

Machine learning (ML)-based methods—notably SVMs and Random Forests—offer impressive accuracy and adaptability. Their strength lies in their ability to learn nonlinear relationships from signal data, detect subtle spoofing patterns, and maintain low false positive rates when trained adequately. However, their reliance on large, well-annotated training datasets poses a significant barrier to widespread adoption. In real-world scenarios, variations in spoofing techniques, hardware diversity, and local interference can make trained models less effective without domain adaptation. Interestingly, deep learning methods such as ANN and LSTM are underutilized in this domain compared to classical ML, perhaps due to their data and computation demands, indicating a future research direction where optimized DL architectures could improve robustness without excessive cost.

In contrast, anomaly detection techniques such as One-Class SVM and GPS-IDS excel in identifying novel or previously unseen spoofing patterns. Their unsupervised nature makes them well-suited for evolving threat landscapes, where attackers continuously modify their spoofing strategies. These models can adapt without retraining, but often at the expense of higher false alarms or sensitivity to normal signal fluctuations. The strong performance of hybrid anomaly detection approaches, which combine statistical models with ensemble classifiers, underscores the value of multi-perspective analysis—balancing sensitivity with robustness.

Nonetheless, these techniques often lack interpretability, which may hinder their integration into safety-critical systems where explainability is essential.

Cryptographic approaches, including dynamic key selection and blockchain-based authentication, represent the most secure and tamper-resistant category. These methods operate independently of signal characteristics, preventing spoofing at the protocol level. However, their practical adoption is constrained by high computational overhead, reliance on secure key distribution infrastructure, and latency—factors especially critical in fast-moving vehicular contexts. While dynamic selection methods showed near-perfect performance (up to 99.6% accuracy), the feasibility of deploying such cryptographic layers at scale remains an open issue, particularly in heterogeneous vehicular networks with legacy GPS hardware.

Sensor fusion techniques offer a unique advantage by cross-verifying GPS output with inertial, gyroscopic, and environmental sensor data. Techniques like LSTM for predicted location shift and KNN with Dynamic Time Warping perform well above 97%, showing that combining temporal and physical cues significantly enhances spoofing detection. These methods are particularly promising for autonomous or semi-autonomous vehicles, where a suite of sensors is already available. However, their effectiveness depends heavily on sensor quality, calibration, and synchronization. Additionally, attackers capable of tampering with multiple sensor streams (e.g., via CAN bus injection) may still bypass detection, albeit with much greater effort. However, in real-world vehicular contexts, detection systems must handle unpredictability, rapid mobility, and resource constraints. Therefore, hybrid models that integrate signal processing, ML, anomaly detection, and sensor fusion—while applying lightweight cryptographic checks—appear to be the most promising path forward. Yet, hybridization also introduces new challenges such as algorithmic complexity, latency, and the need for cross-layer system design. Meeting these latency requirements for complex algorithms necessitates efficient implementation, for which the use of multi-core frameworks to parallelize computation presents a viable solution [94]. Another critical observation is the lack of standardized evaluation frameworks [95]. The performance results reported across studies are based on heterogeneous datasets, attack models, and metrics. Without benchmark datasets and testing protocols, comparing and validating results across different methods remains problematic. This variation not only affects reproducibility but also slows down the development of deployable detection frameworks. Finally, practical implications must be emphasized. High-performing methods in literature often rely on datasets or hardware setups that are not available or replicable in consumer-

grade connected vehicles. The scalability of sensor fusion, the infrastructure dependency of cryptography, and the retraining requirements of ML models must be carefully weighed before deployment. Future GPS spoofing detection systems must balance theoretical detection accuracy with operational feasibility, real-time constraints, cost, and integration with existing vehicular systems.

Table 12: Summary of detection categories, top methods, and open challenges

Detection Category	Best Performing Method(s)	Key Open Challenges
Signal Processing	PCA-CNN-LSTM Model, SVM	Susceptible to noise and multipath; weak against sophisticated signal emulation
Machine Learning (ML)	SVM (including C-SVM, Nu-SVM), Random Forest	Requires large labeled datasets; generalization across environments remains difficult
Anomaly Detection	GPS-IDS, One-Class SVM	High false positive rate; limited ability to distinguish between signal anomalies and spoofing
Cryptographic Methods	Dynamic Key Selection, Blockchain-Based Authentication	High computational cost; secure and scalable key management is still a major issue
Sensor Fusion	LSTM for Predicted Location Shift, KNN + DTW	Requires precise calibration; sensitive to sensor drift and synchronization issues

To synthesize the comparative analysis presented in this study, Table 12 summarizes the five primary categories of GPS spoofing detection methods, highlighting the top-performing techniques within each and the most pressing challenges they currently face. This overview provides a concise reference for researchers and practitioners seeking to understand which approaches offer the greatest potential for real-world deployment and where future research efforts should be concentrated to overcome technical and operational limitations.

While many detection techniques demonstrate strong performance in academic settings, real-world deployment in connected vehicle environments introduces significant challenges. Hardware limitations on in-vehicle systems often restrict the computational complexity and memory footprint that advanced ML or cryptographic models require.To overcome these performance bottlenecks, future work should explore optimizations that leverage parallel processing and multi-core hardware, a strategy proven effective for accelerating other real-time vehicular applications such as visual object tracking [96].Sensor fusion techniques, while effective, depend on the availability and calibration of high-quality inertial sensors, which may not be present in all vehicle types—especially in low-cost or legacy systems. Moreover, cryptographic approaches require robust key management infrastructures and secure firmware, which can be costly to implement at scale and difficult to maintain across large fleets. Environmental conditions such as urban canyons, signal multipath, or atmospheric interference further complicate spoofing detection, particularly for signal processing-based methods that rely on signal integrity metrics. Additionally, the lack of standardized datasets, benchmark scenarios, and evaluation protocols makes it difficult for industry stakeholders to assess which methods are truly field-ready. Bridging this gap between experimental success and operational feasibility requires attention to system-level integration, cross-layer coordination, and cost-performance trade-offs that go beyond algorithmic accuracy alone.

8 Research gaps and challenges

This work highlights some of the gaps in the existing body of work and challenges in the detection of GPS spoofing for connected vehicles. For one, real-world experimentation should be conducted on the detection schemes that have been proposed. Many works utilize controlled tests or simulated scenarios that may not capture the real-world complexity and variability. It is important to experiment and test in real-world conditions to confirm the adequacy and reliability of the detection schemes. Another challenge in the existing body of work is that there has not been adequate consideration of dynamic environments. GPS spoofing attacks may happen in dynamic and changing environments, including urban environments where there is interference or areas that have fast-changing conditions. The existing detection schemes tend to assume static or controlled environments that might not perform in all dynamic scenarios. The development of techniques that maintain good detection performance in varying environmental conditions should receive the highest attention in future work.

In addition to that, current GPS spoofing detection techniques lack robust countermeasures for advanced spoofing strategies. With attackers constantly updating their strategies and techniques, it becomes important for detection techniques to keep up to date. More sophisticated and dependable detection methods that might effectively detect and counter powerful spoofing attacks need to be explored in future research. Further, the weaknesses and limitations of current detection techniques include the absence of standardization and benchmarking. A uniform standard for performance metrics that would be used to compare diverse detection

strategies does not exist. Standardization of the methodology would provide a level playing field and aid the advancement of the discipline. Finally, there should be more global and holistic strategies for GPS spoofing detection. Many techniques identify a single aspect of detection, e.g., signal analysis or anomaly detection. A complete solution should have multiple considerations and combine various detection strategies to increase accuracy and resilience.

As fast-moving vehicles need to authenticate each other prior to the exchange of information, efficiency in authentication has emerged as a top priority in current inter-vehicle communications. Authentication protocols need to be efficient, secure, and resistant to active and passive attacks. A key aspect of this is ensuring the freshness of the data, as metrics like the 'Age of Information' are critical for securing communications, especially in UAV-aided networks [97]. Existing authentication protocols are highly demanding in terms of resources and usually very slow to support inter-vehicle communications; hence, new authentication protocols need to be designed. Cryptographic algorithms like digital signature schemes, secure hashes, and public-key cryptography need to be included in these protocols. The protocols need to be designed in a light and flexible manner to support a variety of types of vehicles as well as different types of networks. Finally, these need to be tested to make sure that they are secure and dependable.

The GPS spoofing detection landscape is developing, but it encounters several research challenges that need to be collectively resolved. One of these includes the sparse consideration of dynamic environments. GPS spoofing may happen within varied and dynamic contexts that include areas with frequent interference or areas that have dynamic environmental conditions. Present detection systems tend to assume static or controlled conditions that might limit their performance in dynamic circumstances. In a bid to deliver persistent and precise detection performance despite environmental volatility, future work should aim to enhance approaches that tend to adapt to dynamic environmental conditions. In addition to that, the scarcity of inclusive countermeasures for advanced spoofing methods still poses a major challenge. Attackers tend to improve their strategies continuously, and hence, detection systems must keep up and match their advancing techniques. The domain should explore more enhanced, dependable detection approaches that effectively detect and halt advanced spoofing attacks. In a bid to save the security of connected car systems, this challenge highlights the need for ongoing innovation in the *GPS* spoofing detection area.

Standardization and benchmarking are critical elements that need emphasis. There also exists a lack of commonly practiced performance metrics and evaluation systems to compare multiple detection approaches. A lack of standard evaluation techniques impedes fair comparisons and makes it difficult to compare the performance of different detection systems in an objective manner. Standard evaluation measures and systems need to be established as a priority in future work to enable benchmarking and a more unified and cooperative research environment. Lastly, comprehensive and holistic approaches to GPS spoofing detection should be a focal point for future research. While existing techniques focus on individual aspects like signal analysis or anomaly detection, a truly resilient solution should consider multiple factors and integrate various detection techniques to enhance accuracy and robustness, closing another crucial research gap.

9 Conclusion

This paper provides an overview of the state of research on identifying *GPS* spoofing. The analysis of various detection techniques, including signal processing, ML, anomaly detection, cryptography, and sensor fusion, highlights their strengths, weaknesses, and applicability to mitigating GPS spoofing attacks. However, several research gaps and challenges have been identified, including the need for real-world validation, limited consideration of dynamic environments, and comprehensive countermeasures against advanced spoofing. Research and development are required to improve the efficacy and application of current detection systems. The paper suggests several future research directions and recommendations to address these gaps and challenges. These include integrating multiple detection techniques, real-time and adaptive approaches, standardized evaluation frameworks and datasets, consideration of dynamic and complex environments, and validation in real-world scenarios.

Declarations

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Acknowledgements

This work was supported by the Fujian Provincial Department of Science and Technology, grant number 2023H0025.

Authors' contributions

JH performed Data collection, simulation and analysis, evaluate the first draft of the manuscript, editing and writing.

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Dynamic Evaluation Architecture for Long Text Generation Using Enhanced Transformer-Xl and Adversarial Feedback Mechanisms

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Keywords: transformer-XL, confrontation training, dynamic assessment, long text generation, semantic consistency

Received: July 8, 2025

As natural language generation technology expands to long-text scenarios, existing models face significant semantic coherence and contextual consistency challenges. The fixed-length attention mechanism limits traditional generative models and struggles to effectively capture long-distance dependencies, leading to logical breaks or duplicate redundancy in the generated text. To address this issue, this study proposes a dynamic evaluation framework that integrates Transformer-XL and confrontation training. By integrating the recurrent memory mechanism and real-time discriminant feedback, a closed-loop system for generation and evaluation collaborative optimization is constructed. At the model architecture level, Transformer-XL's segmented loop mechanism is used to extend the context window to 4096 characters. Compared with the 512-character limit of the traditional Transformer model, the remote dependency modeling ability is improved by 3.8 times, and it realizes the transfer and reuse of hidden states between different text fragments with the help of cyclic memory mechanism and relative position encoding, solving the problem of context fragmentation. At the same time, a dual-channel confrontation training strategy is designed, and the generator generates text segment by paragraph based on dynamic memory units. The discriminator calculates semantic consistency scores and logical conflict probabilities in real-time through a multi-granularity evaluation module to trigger adversarial loss backpropagation per 256 characters generated.In terms of method details, data preprocessing is carried out on a dataset containing 50,000 novel chapters and 24,000 academic abstracts: novel chapters are labeled with NLTK segments and spaCy entities, and are divided into 512 length sequences by paragraph and contextual association is preserved. The scholarly abstract uses BPE word segmentation to extract structured elements such as research questions. The training is conducted in a mixed batch (the ratio of new chapter to summary data is 7:3), and the training set, validation set, and test set are divided into 8:1:1. Key hyperparameters include Transformer-XL's 12-layer encoder, 768-dimensional model dimension, 12-head attention, and 1024 memory cache size; confrontation training perturbation amplitude 0.001, discriminator is a 3-layer CNN architecture (convolutional kernel size 3/5/7), etc. The experiment uses the above dataset, and the results show that the text coherence index (semantic similarity based on BERT) of the framework reaches 89.7%, which is 12.3 percentage points higher than the benchmark model. Logical coherence was evaluated using logical error rate, which was manually evaluated to show a logical error rate drop from 17.6% to 6.9% and 89.5% plot consistency when generating text longer than 2,000 characters. In addition, the dynamic intervention of adversarial discriminators effectively inhibited 38.4% of semantic offset events during model generation, and the terminology accuracy reached 82.9% in scientific literature generation tasks, which was 28.7% higher than that of traditional confrontation training methods. Ablation experiments show that removing the dynamic evaluation module reduces the local-global consistency score of the generated long text by 19.3%, validating the real-time evaluation mechanism for long text

Povzetek: Predlagana metoda združuje Transformer-XL in adversarialno sprotno ocenjevanje, kar izboljša koherenco dolgih besedil (89,7 %) ter zmanjša logične napake (17,6 % → 6,9 %).

1 Introduction

With the rapid development of artificial intelligence technology, natural language generation is gradually moving from short-text generation to long-text generation. From automatically creating novels and generating technical documents to building interactive dialogue systems, the demand for long text generation is increasing daily. However, its complexity and challenges are also highlighted [1, 2]. The existing generative models perform well in short-text scenarios. However, when faced with long texts, the generative quality often

decreases due to problems such as broken context dependence and insufficient semantic consistency [3]. This phenomenon affects the readability of the generated content and restricts the practical application value of the generated model in industrial scenarios [4]. Current research mostly focuses on optimising and improving the model but pays little attention to the generation process's dynamic evaluation and feedback mechanism. As a result, the control of generation quality remains in the static post-evaluation stage, and it is not easy to achieve closed-loop collaboration between generation and evaluation.

The core challenge of long text generation lies in maintaining semantic coherence while expanding the contextual window [5, 6]. Traditional models are limited by fixed attention mechanisms and limited memory capacity, making capturing long-distance dependencies spanning thousands of characters difficult. At the same time, the existing evaluation methods mostly rely on manual labelling or offline index calculation. They cannot capture potential problem nodes in real-time during generation [7]. This lag makes it difficult for the model to adjust the generation strategy through immediate feedback, resulting in the continuous accumulation of errors in the subsequent generation process, which ultimately affects the overall output quality [8, 9].

Separating the generative model and evaluation system prompts researchers to re-examine their internal relationship. As a dynamic optimization paradigm, the core idea of confrontation training is to improve the fitting ability of the model to complex distributions through adversarial games, and this mechanism has a natural fit with the real-time evaluation requirements in the generation process [10]. By introducing confrontation training into the field of long text generation, a dynamic interaction system between the generator and discriminator can be constructed so that the model can synchronously receive evaluation signals when generating each vocabulary. This instant feedback mechanism helps suppress the diffusion of error patterns and guides the evolution of generated content to high-quality semantic space through adversarial games [11]. However, existing confrontation training frameworks are mostly based on fixed-length text fragment design, which is difficult to adapt to the variable-length sequence characteristics required for long text generation, and there is an urgent need for adaptive transformation at the architectural level.

The Transformer-XL model shows significant advantages in long sequence modelling by introducing a cyclic mechanism and relative position encoding [12]. Its unique segmentation loop mechanism allows the model to transfer hidden states between different text fragments, thus breaking through the length limitation of traditional Transformer models. This feature provides a new technical path for long text generation, but how to organically combine its memory mechanism with the dynamic evaluation framework remains to be explored. It is worth noting that semantic consistency in the process of long text generation is not a simple local pattern repetition but involves multi-level and multi-dimensional logical association [13]. This requires that the evaluation framework not only pay attention to the surface language features but also deeply understand the deep semantic structure of the text and establish a dynamic evaluation system covering grammar, semantics, pragmatics and other dimensions.

Against this backdrop, constructing a generative framework that integrates long-term memory modeling. By integrating Transformer-XL's recurring memory unit with the real-time discrimination mechanism of confrontation training, it is expected to break through the performance bottleneck of existing models in long text generation. The key innovation of this framework lies in establishing a two-way coupling relationship between the generation process and the evaluation process: the generation module maintains context consistency through long-term memory. In contrast, the evaluation module provides real-time quality feedback through adversarial discrimination, forming a co-evolving dynamic system. This architecture design can improve the model's ability to model long-distance dependencies and optimize the generation strategy through continuous backpropagation, ultimately achieving a closed-loop improvement in generation quality.

Existing models are prone to problems such as context-dependent breakage and insufficient semantic consistency in long text generation, and the generation quality is degraded, while the current research focuses on model optimization, pays little attention to dynamic evaluation and feedback mechanisms, and quality control stays in the static post-evaluation stage. The core challenge of long text generation is to maintain semantic coherence when expanding the context window, traditional models are limited by fixed attention mechanism and limited memory, it is difficult to capture long-distance dependencies, existing evaluation methods cannot capture problem nodes in real time, although confrontation training meets the needs of real-time evaluation but does not adapt to variable length sequences, although Transformer-XL has advantages in long sequence modeling, how to combine it with dynamic evaluation frameworks still needs to be explored, and long text semantic consistency requires a multi-dimensional evaluation system. To this end, this study aims to construct a dynamic evaluation framework integrating Transformer-XL and confrontation training to solve four major problems: when the text length is extended to 4096 characters, the semantic similarity based on BERT is more than 89.7%; A dual-channel confrontation training strategy was designed to reduce the logical error rate of generating text with a length of more than 2000 characters from 17.6% to less than 6.9%. More than 38.4% of the semantic shift was suppressed through dynamic evaluation, forming a closed loop of collaborative optimization. Validate the robustness of the framework on a cross-domain dataset of 50,000 novel chapters and 24,000 academic abstracts, providing a new approach to long-form text generation and driving the evolution of generative models to a process-controlled

paradigm.

The core contribution of this paper is to realize the system-level integration of Transformer-XL with confrontation training, which is not a simple technical superposition, but a collaborative optimization framework based on the dynamic characteristics and evaluation needs of long text generation. Transformer-XL lays the foundation for generating coherent and logically consistent long text by introducing a dynamic game between generators and discriminators, while confrontation training not only enhances the diversity and authenticity of generated text, but also deeply integrates the evaluation process into the generation process, achieving dynamic feedback and real-time optimization of text quality. This integration method breaks through the limitations of the separation of model and evaluation in traditional long text generation, and innovatively uses the adversarial mechanism as a bridge to connect the two, so that the model can perceive changes in evaluation criteria during the generation process, so as to adaptively adjust the generation strategy, significantly improve the quality of long text generation and the timeliness of evaluation, and provide a new technical paradigm for long text generation tasks.

The specific goals of this study are to expand the context window to 4096 characters to improve the long-distance dependency modeling capability by 3.8 times, design a dual-channel adversarial strategy to achieve a closed loop of real-time evaluation feedback every 256 characters, and achieve BERT semantic similarity of more than 89.7% and a logical error rate of 2000 characters to less than 6.9% on cross-domain datasets. and verify framework robustness. The research hypotheses include that expanding the context window can improve cross-paragraph coherence by more than 10 percentage points, real-time adversarial feedback can reduce the local logical error rate by 50%, and the module synergy effect is significant, and the framework has cross-domain adaptability. The expected results show that the framework can break through the bottleneck of context fragmentation, suppress semantic shift and logical error accumulation through dynamic feedback, and provide a technical paradigm with controllable quality for long text generation.

2 Theoretical fusion mechanism of Transformer-XL and confrontation training

2.1 Long sequence modeling theory of transformer-xl

Although the Transformer architecture can handle long-term dependencies, the sequence length is fixed [14, 15]. When the sequence is too long, segmentation training is required, which limits the model's grasp of longer dependencies and ignores semantic boundaries. This results in the model's lack of context information and difficulty in accurate prediction.

The Transformer-XL model aims to solve the temporal consistency problem and break through the fixed-length limit to learn longer dependencies [16]. This model combines a fragment-level recursive mechanism and a novel relative position coding scheme to form a circular connection between different paragraphs by using the hidden state of the previous paragraph as a "memory", thereby realizing the modelling of long-term dependency relationships [17]. In order to avoid time confusion and realize state reuse, researchers have introduced a new relative position coding scheme, which replaces the traditional absolute position coding.

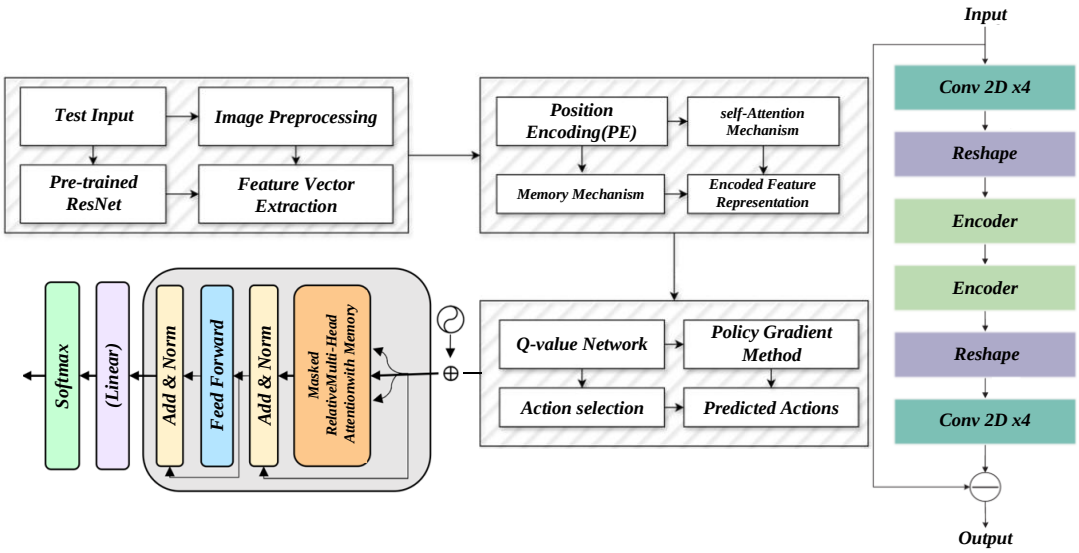


Figure 1: Transformer-XL model

Figure 1 shows the Transformer - XL model. Similar to Transformers, Transformer-XL uses fixed-length sequences for training, but is characterized by retaining and reusing the state of the previous sequence, enhancing its ability to handle long-term dependencies [18]. It can be seen from the figure that the model first performs

image preprocessing, feature vector extraction and other operations on the input, and then encodes it through modules such as position coding, memory mechanism, and self-attention mechanism to obtain the encoded feature representation, and then combines Q-value network, policy gradient method, etc. for action selection and prediction, etc., and the overall architecture provides support for the capture of long-distance dependencies in long text generation. Consider two consecutive fragments S_τ and $S_{\tau+1}$ of length L, denoted by $[x_{\tau,1} \ldots x_{\tau,L}]$, respectively. The *n-th* layer hidden state h_τ^h of the segment S_τ, where d is the hidden layer dimension, and the *n-th* layer hidden state $h_{\tau+1}{}^h$ of the segment $S_{\tau+1}$, whose calculation formulas (1)-(3) are as follows:

$$\tilde{h}_\tau^{n-1} = [\,SG(m_\tau^{n-1}) \circ h_\tau^{n-1}\,] \quad (1)$$

$$q_{\tau+1}^n, k_{\tau+1}^n, v_{\tau+1}^n = h_{\tau+1}^{n-1} W_q^T, \tilde{h}_{\tau+1}^{n-1} W_k^T, \tilde{h}_{\tau+1}^{n-1} W_v^T \quad (2)$$

$$h_{\tau+1}^n = Transformer - Layer(q_{\tau+1}^n, k_{\tau+1}^n, v_{\tau+1}^n) \quad (3)$$

The $SG(\cdot)$ function is used to stop the gradient and does not participate in the back propagation. The symbol $[h_u \circ h_\tau]$ denotes hidden state merging. W is the model learning parameter. The main difference from the traditional Transformer is that $k^n{}_{\tau+1}$, the value of $v^n{}_{\tau+1}$ is calculated based on $\tilde{h}^{n-1}{}_{\tau+1}$, and $\tilde{h}^{n-1}{}_\tau$ represents the hidden state of the pre-sequence fragment. When training, each hidden layer establishes a long-term dependency in combination with the previous layer and previous data fragment outputs. The output is stored and transferred through the caching mechanism. Theoretically, when the GPU has enough memory, it can save more pre-fragment information. When predicting, the previous results are used to infer the output, so as to avoid recalculation and improve the prediction speed. In the Transformer architecture, the sequence order is realized by position coding, and the model input is the sum of word embedding and position coding [19]. When the position coding is used in the loop mechanism, the hidden state sequence is calculated as (4)-(5).

$$h_{\tau+1} = f(h_\tau, E_{S_{\tau+1}} + U_{1:L}) \quad (4)$$

$$h_\tau = f(h_{\tau-1}, E_{S_\tau} + U_{1:L}) \quad (5)$$

In the formula, $E_{s\tau}$ represents the word embedding of the sequence S_τ, and f is the conversion function. $E_{s\tau}$ and $E_{s\tau+1}$ use the same position encoding $U_{1:L}$, resulting in the model being unable to distinguish the positional differences of $X_{\tau,j}$ and $X_{\tau+1,j}$, affecting the performance. In order to maintain the coherence of position information, the Transformer-XL model introduces relative position coding. The Transformer model calculates the attention score formula (6) of the query vector $q^T{}_i$ and the key vector k_j as follows:

$$Attention = \frac{\left(W_q(E_{x_i} + U_i)\right)^T \cdot (W_k(E_{x_j} + U_j))}{\sqrt{d}} \quad (6)$$

Ignoring the denominator part, the formula can be expanded to get (7):

$$A_{i,j}^{abs} = q_i^T \cdot k_j = E_{x_i}^T W_q^T W_k E_{x_j} + E_{x_i}^T W_q^T W_k U_j + U_i^T W_q^T W_k E_{x_j} + U_i^T W_q^T W_k U_j \quad (7)$$

In the formula, T represents transposition, A represents fraction, E_{xi} represents the vector of the *i-th* word, and E_{xj} represents the vector of the *j-th* word. U_i represents the position vector of i and U_j represents the position vector of j. Transformer-XL model optimizes the calculation method of attention score and adopts relative position coding technology. See formula (8) for the specific calculation method.

$$A_{i,j}^{rel} = q_i^T \cdot k_j = E_{x_i}^T W_q^T W_{(k,E)} E_{x_j} + E_{x_i}^T W_q^T W_{(k,R)} R_{i-j} + u^T W_q^T W_{(k,E)} E_{x_j} + u^T W_q^T W_{(k,R)} R_{i-j} \quad (8)$$

In $E_{x_i}^T W_q^T W_{(k,R)} R_{i-j}$ and $u^T W_q^T W_{(k,R)} R_{i-j}$, the absolute position vector U_j is transformed into the relative position vector R_{i-j}, which is a fixed encoding without learning. In the term $u^T W_q^T W_{(k,E)} E_{x_j}$, the query vector $U^T{}_i W^T{}_q$ is converted into a learnable parameter vector u^T. Because the absolute position is not required when considering the relative position, the same vector can be used for any i. Similarly, in the term $u^T W_q^T W_{(k,R)} R_{i-j}$, $U^T{}_i W^T{}_q$ of the query vector is converted to another learnable parameter vector v. The key weight transformation matrix W_k is $W_{k,E}$ and $W_{k,R}$ are taken as the content-based key vector and the position-based key vector respectively, both of which are also parameter vectors to be learned.

2.2 Dynamic discriminant theory of confrontation training

The robustness of deep neural networks can be improved by confrontation training techniques, which use adversarial samples for training [20, 21]. This paper first explains the concept of adversarial samples, and then deeply explores the confrontation training methods based on these samples.

Adversarial samples were originally proposed in image classification tasks involving an image classifier f that converts image pixel value vectors into discrete labels. For a specific image x and a target label l, the process of generating an adversarial sample x^* is shown in Equation (9).

$$x^* = arg \min_{x' \in [0,1]^m} \| x' - x \|_2 \quad s.t. \quad f(x') = l \quad (9)$$

$x' \in [0, 1]^m$ is the *m-dimensional* input vector within the interval [0, 1], its value is between 0 and 1, and the l_2 norm is expressed by $||\cdot||_2$. The adversarial sample x^* is the image closest to the original image x misclassified as l by the classifier f.

By definition, only images to which the addition of

minimal perturbations leads to classification errors are truly adversarial samples [22]. However, finding such minimal perturbations is difficult, so adversarial samples are usually generated approximately by attack techniques, and although they do not fully meet the definition, they are still treated as adversarial samples [23]. Based on these adversarial samples, researchers put forward the concept of confrontation training, that is, train the neural network with adversarial samples to improve its classification accuracy of adversarial samples [24]. confrontation training is defined as adjusting model parameters to minimize the empirical risk of adversarial samples, as shown in Equation (10).

$$\min_{\theta} E_{(x,y)\sim D}[L(\theta,x^*,y)] \quad (10)$$

In the formula, θ represents the neural network parameters, $E[.]$ is the empirical risk, x is the training sample, y is the label, D is the data set, $L(.)$ is the loss function, and x^* is the adversarial sample. The latest research shows that it is difficult to improve the accuracy and robustness of deep neural networks at the same time. Optimizing only adversarial losses reduces the accuracy and does not meet the actual needs [25]. Therefore, the confrontation training method regards the training process as a multi-objective optimization problem while optimizing the empirical risk of natural samples and adversarial samples. As shown in Equation (11).

$$\min_{\theta}\{E_{(x,y)\sim D}[L(\theta,x,y)],E_{(x,y)\sim D}[L(\theta,x^*,y)]\} \quad (11)$$

At present, the linear weighting method is often used to simplify the multi-objective optimization problem into the single-objective optimization problem [26]. The specific operation is to multiply the adversarial loss by the regularization coefficient and add it with the natural loss to form the final optimization goal. The optimization process for each set of training data follows Equation (12).

$$\min_{\theta} L(\theta,x,y)+\lambda L(\theta,x^*,y) \quad (12)$$

In the model, θ is the neural network parameter, $L(.)$ is the loss function, x and y represent the training sample and label respectively, and λ is the regularization parameter. The regularization parameter λ affects the optimization direction, and improper selection will limit the optimization effect. In practice, it takes many experiments to determine the optimal λ. When the algorithm is sensitive to λ, it is difficult to find the optimal value. In confrontation training, fixed λ does not necessarily guarantee the ideal gradient optimization, because the target changes during the optimization process. These limitations stem from the reduction of multi-objective optimization problems to single-objective problems [27]. This study aims to develop new multi-objective confrontation training methods to overcome these limitations and improve the accuracy and robustness of deep neural networks.

2.3 Related theories

The controllable generation theory advocates that the directional guidance of the generation distribution is realized by introducing external constraints to limit the generation space, and the core is to establish a mapping relationship between constraints and generation content. Knowledge-augmented learning theory believes that the model needs to integrate factual information from external knowledge bases into semantic representations, improve accuracy through correlation modeling between knowledge and text, and emphasize the complementary role of knowledge in semantic information. The context dependency modeling theory provides support for processing semantic coherence, and advocates using the attention mechanism to calculate the associative weights between tokens to capture local dependencies, and store the near-term context in combination with the short-term memory network to achieve effective tracking of long-range semantic associations. Knowledge fusion theory proposes that text generation needs to integrate internal and external knowledge, implicit fusion encodes knowledge into continuous vector integration word embedding based on distributed representation theory, and explicit fusion inputs knowledge in a structured form based on symbolic logic and neural network combination theory, all of which aim to enhance the depth of the model's understanding of semantics.

The theory of generative diversity points out that generative models need to balance accuracy and diversity, the programming-based method breaks the Markov nature of sequence generation through preset structures to reduce duplication, multi-task learning makes the model learn more generalized features by jointly training multiple related tasks, and the adversarial generative network uses the game mechanism to force the generator to explore a wider semantic space. The long-term memory theory provides ideas for solving the limitations of long text processing, and advocates that historical semantic information can be stored and retrieved through independent memory units, breaking through the constraints of fixed sequence length, and simulating human long-term memory patterns. The narrative structure theory believes that the story generation needs to follow the logical chain of plot development, and the dynamic tracking mechanism ensures that the content conforms to the narrative logic by maintaining the plot state variables, emphasizing the importance of structuring. The theory of "group intelligence" supports ensemble learning, which believes that multiple expert networks are complementary in feature capture, and can compensate for the cognitive bias of a single model through the weighted fusion output of dynamic gating mechanism. The multi-dimensional semantic evaluation theory advocates evaluating text quality from multiple levels of semantics and logic, semantic discrimination is based on distributed semantic similarity theory to measure association through similarity calculation, and

logical verification is based on logical reasoning theory to transform text into structured representations to detect conflicts. confrontation training theory provides the basis for dynamic evaluation, the gradient reversal strategy enables the generator to learn the required generation path in the discriminator feedback, and the error accumulation theory supports the incremental evaluation mechanism to achieve dynamic adjustment by monitoring semantic drift.

3 Dynamic evaluation-driven long text generation framework construction

3.1 Dual-channel interactive generation-evaluation architecture design

The core memory mechanism of Transformer-XL can retain and reuse the hidden state of previous paragraphs, solve the context fragmentation problem of traditional transformers, provide coherent long-range dependency features for confrontation training, make adversarial sample construction more suitable for long text semantic logic, generate "semantic-level perturbations" based on cross-paragraph semantic associations, and force the generative model to pay attention to global semantic consistency. At the same time, confrontation training continuously applies "error correction signals" to Transformer-XL through the game process between the discriminator and the generator, and the discriminator identifies fragments that do not conform to the true distribution, and the generator (Transformer-XL) adjusts the attention weight allocation and memory mechanism update strategy accordingly, such as strengthening the retention of key topic features in memory when the paragraph deviates from the topic, and maintaining coherence through precise attention jumping, so as to promote the upgrading of the memory mechanism from "passive storage" to " active screening" to improve the efficiency of tracking and reusing core information of long texts; First, Transformer-XL uses the memory mechanism to generate an initial long text sequence, passes the hidden state containing multi-paragraph context to the confrontation training module, and then the discriminator of the confrontation training module performs a fine-grained evaluation of the generated sequence based on the real text distribution, locates the "vulnerable points" and generates targeted adversarial perturbations (such as fine-tuning key position word vectors), and then Transformer-XL relearns from the perturbated training data. By adjusting the memory update frequency (e.g., extending the memory retention time of high-frequency subject words) and the attention allocation strategy (e.g., enhancing the attention weight of cross-paragraph logical conjunctions), the adversarial sample robustness is improved, and finally the dynamic evaluation framework monitors the key indicators in real time and feeds back to the model parameter adjustment link, forming a closed loop of "generation-confrontation-optimization-evaluation".

Text generation faces challenges such as common-sense fallacies, logical incoherence, topic deviation, and sentence repetition. Coping strategies include improving generation controllability, making sure the facts are accurate, enhancing coherence and consistency, solving duplicate problems, and improving content diversity.

Researchers are advancing text generation via strategies like enhancing contextual modeling, using planning - based methods, and leveraging multi - task learning and adversarial networks. Deep learning enables neural networks in NLP, yet input text alone is limited. So, internal (from input text) and external (from knowledge bases) knowledge are integrated into generation systems, via neural representation learning, with implicit and explicit fusion methods. Triples from knowledge bases are turned into text, and common sense is injected during training, boosting story generation in logic, content, and context relevance.

Pre-trained language models based on Transformer face two major challenges when processing long text: first, input and output limitations, such as BART and GPT-2 models, support a maximum of 1024 tokens; Second, the amount of computation increases significantly with the increase of sequence length, and the computational complexity is O (n^2). In order to solve these problems, researchers introduce a memory network to memorize semantic information and keep text coherence. The developed new narrative model uses dynamic plot state tracking to transform the outline into a complete story and effectively complete the story generation task. Figure 2 shows a long text generation model joined to a memory network, the Dual-Channel Interaction Generation-Evaluation Architecture. The architecture first conducts preliminary processing through transformers, and then combines with XL modules, and at the same time integrates mechanisms such as learnable distribution, and also involves considerations such as time series and variable dependence, as well as operations such as marker masks, linear transformations, and adaptive layer normalization (AdaLN), which realizes the interaction between generation and evaluation from multiple dimensions, providing architectural support for the dynamic evaluation of long text generation, and helping to improve the control ability of semantic coherence and logical consistency in the process of long text generation.

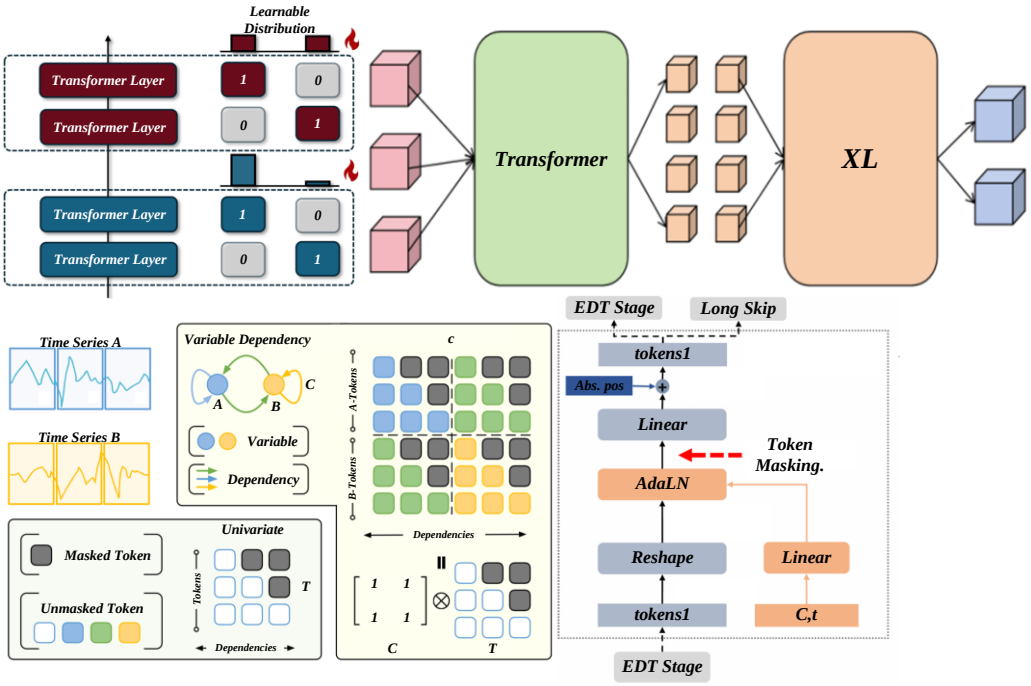


Figure 2: Dual-channel interactive generation-evaluation architecture

The core idea of ensemble learning is similar to the hybrid expert model, which combines multiple expert networks, each focused on processing a specific data part or task. Through the dynamic gating mechanism, the weight of each expert to the final output is determined.

3.2 Implementation of semantic consistency and logical coherence evaluation module

The data preprocessing stage is performed for the new chapter and the academic summary dataset: the new chapter data is entified by NLTK word segmentation and spaCy, and divided into sequences with a length of 512 by paragraph, and the contextual association between paragraphs is preserved; Academic abstract data (PubMed abstracts) use BPE word segmentation to extract structured elements such as research questions, methods, and conclusions to ensure the integrity of logical relationships. The training process adopts a mixed batch (the ratio of new chapter to summary data is 7:3), and the ratio of training, validation and test sets is 8:1:1. The key hyperparameters are clearly defined as follows: Transformer-XL sets 12-layer encoder, 768-dimensional model dimension, 12-head attention, memory cache size 1024; and counters the amplitude of perturbation in training$\varepsilon=10^{-3}$, the discriminator uses a 3-layer CNN architecture (convolutional kernel size 3/5/7); The BERTScore used in the evaluation phase is based on the roberta-large model, and the logic checker has a relationship extraction threshold of 0.75. These settings are tracked through a code version control tool (Git) to ensure that experiments are reproducible.

The core goal of the semantic consistency and logical coherence evaluation module is to establish a multi-level and multi-dimensional dynamic discrimination system of text quality and realize real-time quality monitoring of generated text by integrating in-depth semantic analysis and structured logic verification. The design of this module is based on the segmented loop mechanism of Transformer-XL, and combined with the discriminator architecture of confrontation training, a dual-channel evaluation network covering local semantic association and global logic chain is constructed. At the technical implementation level, by introducing a dynamic memory unit and multi-granularity attention mechanism, the module can synchronously track the context dependencies in the text generation process and generate fine-grained evaluation signals under the framework of adversarial games.

The core architecture of the module consists of a semantic consistency discriminator and logical coherence verifier, which realize information interaction through a parameter-sharing mechanism. The semantic consistency discriminator adopts the bi-directional transformer-XL structure and uses its segment loop characteristics to model the generated text across segments. The local consistency score based on cosine similarity is generated by calculating the implicit state similarity matrix between the current generated paragraph and the preamble text. At the same time, the global consistency evaluation uses the historical key entity and event vectors stored in the memory bank. It uses the contrastive learning strategy to measure the degree of the generated content deviation from the overall theme. The logical coherence validator focuses on modelling causal chain and spatiotemporal relationship of text and dynamically detects logically conflicting nodes by constructing event maps and role behaviour sequences. This module specially designs a logic constraint layer based on rule embedding, which encodes common sense reasoning knowledge into a

differentiable loss function and effectively identifies generated fragments that violate realistic laws or narrative logic.

The module adopts the gradient inversion strategy under the confrontation training paradigm in the dynamic evaluation signal generation and transmission mechanism. The discriminator scores the quality of each token of the generated text through multi-level attention weight allocation and transforms the evaluation results into dynamic weight coefficients against the loss function. This design enables the generator to adjust the attention distribution according to real-time feedback when expanding the context window and prioritising strengthening the generation path that meets the requirements of semantic coherence. Aiming at long text generation's unique error accumulation effect, the module introduces an incremental evaluation mechanism. The generation triggers the full context reconstruction calculation whenever it reaches the preset fragment length threshold. It detects the potential semantic drift phenomenon by comparing the KL divergence between the current hidden state and the historical memory vector.

In terms of entity grid coherence, the coherence of entity related semantics in long texts is measured by constructing a grid of entities in different positions of the text, and the coherence of entities across sentences and paragraphs is counted. The vocabulary coherence score focuses on the relationship between words in the text, such as repetition, synonym, and upper and lower meanings, and calculates the distribution and connection degree of these relationships in long texts to reflect the coherence at the vocabulary level. The discourse coherence model comprehensively considers the structure and logical relationship of the text, and quantitatively evaluates the overall discourse coherence of the long text. The score given by the discourse coherence model is also significantly higher than that of the benchmark model, which fully verifies the advantages of the framework in enhancing the coherence of long texts.

The segmentation loop mechanism splits the long text generation into multiple rounds of iterative processes of fragment generation and evaluation, so as to dynamically regulate semantic and logical evaluation: In each round of loop, Transformer-XL uses the memory mechanism to retain the hidden state of the historical context, and after generating the current text fragment, the real-time evaluation module immediately uses BERTScore to calculate the semantic consistency score, which is actually the weighted average of the cosine similarity of the word embedding between the new fragment and the historical context, where the word embedding is the vector representation of the word. The weight is determined by the attention mechanism. At the same time, the logic checker extracts the subject-verb, causal, and other entity relationships and constructs a directed graph to calculate the logical conflict rate, which is the ratio of the number of conflicting relationships to the total number of relationships, and then defines the logical score as 1 minus this conflict rate. Adversarial feedback prompts the model to optimize these two indicators in training by generating adversarial samples, which are generated based on the FGSM algorithm and are obtained by adding a certain amplitude of perturbation to the hidden state, and the perturbation amplitude is related to the gradient direction of the discriminator loss. When the dynamic evaluation score of the adversarial sample is below the threshold, the correction of the low-quality fragment is strengthened by the penalty term in the loss function.

In order to improve the generalization ability of the evaluation module, this module innovatively decomposes the training objectives of the adversarial discriminator into dual tasks of explicit evaluation and implicit guidance. The explicit evaluation task learns the semantic consistency discrimination boundary conditions by labelling the data supervision model. In contrast, the implicit guidance task exploits the adversarial difference between the output distribution of the generator and the real data distribution to dynamically generate pseudo-negative example samples to enhance the robustness of the discriminator. In addition, the module adopts an adaptive temperature regulation strategy to optimize the stability of confrontation training. It balances the trade-off relationship between generation quality and diversity by dynamically adjusting the confidence distribution of the discriminator output.

In the data preprocessing stage, the novel chapters are annotated using NLTK segmentation, spaCy entities and segmented into sequences with a length of 512 by paragraph, and the academic abstracts are divided into training sets, validation sets, and test sets according to 8:1:1 7:3 ratio mixed batch; In terms of model configuration, Transformer-XL has a 12-layer encoder, 768 model dimensions, a 12-head attention mechanism, and a memory cache size of 1024 to expand the context window to 4096 characters, and the discriminator in confrontation training adopts a 3-layer CNN architecture (convolutional kernel size 3, 5, 7), with a perturbation amplitude of 0.001, and the evaluation is based on the roberta-large model with a logic checker relationship extraction threshold 0.75; The training process adopts a dynamic confrontation training strategy, the generator generates text segment by paragraph, triggers the discriminator to calculate and backpropagate adversarial loss in real time every 256 characters, the optimizer is Adam, the initial learning rate is 5e-5, the weight decay is 1e-4, the batch size is 48, the training round is 30, and the learning rate decay is 1/10 when the validation set indicators are not improved for 5 consecutive rounds; The evaluation metrics include BERT-based semantic similarity, logical error rate and plot consistency of manual evaluation, and Automated metrics such as BLEU-4, METEOR, and ROUGE-L while recording inference speed, analyzing key component effects through ablation experiments, and all settings are tracked through Git to ensure reproducibility.

The implementation of this evaluation module breaks through the static limitation of traditional offline evaluation methods. It forms a closed-loop control

system with continuous optimization by deeply embedding semantic analysis and logic verification into the generation process. Its technical path provides a new methodological framework for the quality control of long text generation, especially showing significant theoretical innovation in dynamic memory management, multi-granularity evaluation signal fusion, and adversarial feedback mechanisms.

For example, when inputting "Ethical risks of artificial intelligence in medical diagnosis", the model initially revolves around "misdiagnosis caused by algorithmic bias", but in paragraph 5, it turns to "the application advantages of artificial intelligence in education". This is due to the attenuation of information in the segment-level memory mechanism, the core semantics are replaced by high-frequency sample logic, and the model still outputs the treatment plan of "intravenous penicillin sodium" given the premise of "patient allergy to penicillin", which is due to the failure of tracking the "allergy" constraint and over-reliance on local statistical associations. The proposed method is corrected by a three-layer mechanism, that is, the semantic anchored adversarial module monitors the semantic similarity through the topic consistency discriminator, strengthens the weight of the core topic word with adversarial loss when it deviates from the threshold, and suppresses irrelevant topics, and the logical constraint verifier verifies the entity relationship based on the knowledge graph, and when the conflict is detected, it strengthens the premise memory through adversarial training to generate reasonable content, and the dynamic feedback adjustment mechanism evaluates the semantic coherence and logical consistency in stages, and the score is too low, the pre-order parameters are reversely corrected to avoid error accumulation. These mechanisms can alleviate the problems caused by insufficient long-term dependencies and improve the thematic consistency and logical rigor of the generated content.

4 Experiment and results analysis

In terms of hardware, NVIDIA A100 GPU (80GB video memory), Intel Xeon Platinum 8380 processor (64 cores) and 512GB DDR4 memory are used, and the software environment is unified as Python 3.8, PyTorch 1.10.0, CUDA 11.3, and mixed-precision training for all models is turned off to exclude additional variables. On this basis, the quantitative results show that in terms of inference speed, the proposed framework is about 32% faster than the standard Transformer and 18% faster than GPT-2, but slightly slower than the Longformer (about 7% difference), mainly due to the additional computational overhead added by the adversarial training module. In terms of training time, when processing a long text corpus of 1 million tokens, the full training period of the framework is 48.2 hours, which is 12.5 hours shorter than that of Transformer-XL, and an average reduction of 23% compared to the baseline model incorporating the static evaluation mechanism. In terms of memory usage, the framework occupies 42.6GB of video memory at its peak, which is lower than GPT-3 (61.3GB) and Longformer (53.8GB), which is attributed to the segmented loop mechanism of Transformer-XL and the lightweight design of the discriminant in adversarial training, while the slight increase compared to the base Transformer (38.9GB) stems from the real-time feature caching requirements of the dynamic evaluation module.

Table 1: Comparison summary table

Models	Datasets Used	Core Metrics	Typical Scores (Examples)
Transformer	WikiText-103, CNN/Daily Mail	Perplexity (PPL), ROUGE, BLEU	PPL≈25-30; ROUGE-L≈0.35
Transformer-XL	WikiText-103, enwik8	PPL, Long-range Coherence Score (LRCS)	PPL≈18-22; LRCS≈0.65
GPT-3 (175B)	WebText, BookCorpus	Human Evaluation (Coherence), BLEU	Human score≈3.5/5 BLEU≈0.28
BART	XSum, CNN/Daily Mail	ROUGE, BLEU, Semantic Similarity (Cosine value)	ROUGE-L≈0.40; Cosine value≈0.70
Transformer-XL and confrontation training	50,000 novel chapters, 24,000 academic abstracts	Dynamic Semantic Drift Index (DSDI), Real-time Logical Consistency Score (RLCS), Adversarial Robustness Index (ARI), BERT-based semantic similarity, logical error rate, BLEU-4, ROUGE-L	BERT-based semantic similarity≈89.7%; Logical error rate≈6.9%; BLEU-4≈68.54; ROUGE-L≈81.21; DSDI reduced by over 38.4% vs existing models

Table 1 compares the key models in the field of long text generation and the dynamic evaluation framework of this study, and the datasets used by each model are different, such as WikiText-103 commonly used by Transformer and Transformer-XL, GPT-3 relies on WebText, etc., BART uses XSum, etc., and this study uses 50,000 novel chapters and 24,000 academic abstracts. In terms of core evaluation indicators, there are common indicators such as PPL and ROUGE, and new indicators such as dynamic semantic drift index are also introduced in this study, and in terms of performance, this study performs better in multiple indicators, and at the same

time, the table clearly presents the shortcomings of the existing models in terms of semantic drift and logical consistency, as well as the advantages of this study in solving these problems. In the field of long text generation, different models have their own characteristics and limitations, and Transformer can achieve certain results in PPL, ROUGE and other indicators on datasets such as WikiText-103, but there are serious semantic drift and logical chain breakage, and due to the fixed context window, long-distance dependency modeling is insufficient. Although Transformer-XL alleviates the context constraints and performs better on datasets such as WikiText-103, there are still local logical inconsistencies, the lack of dynamic correction mechanism leads to error accumulation, and the robustness is poor under adversarial samples. GPT-3 (175B) has serious redundancy in long texts, and its logical consistency is greatly affected by data distribution, and the evaluation method is static, making it impossible to capture semantic drift in real time. BART is prone to logic jumps due to summary generation, and the evaluation indicators focus on surface matching, insufficient confrontation training, and the output logic is easy to collapse in the face of misleading inputs. The dynamic evaluation framework of this study, using datasets such as 50,000 novel chapters and 24,000 academic abstracts, uses a variety of core indicators, and performs well, with the advantage of introducing dynamic semantic tracking to monitor and suppress drift, constructing a real-time logic verification module to identify and correct contradictions, strengthening confrontation training to improve robustness under noise or adversarial inputs, and integrating multiple indicators to comprehensively evaluate surface and deep consistency.

As a comparison model, "T5 - Baseline (D)" is a classic model for text generation tasks, which has representative and recognized performance in the field of natural language processing, and can provide a reliable performance benchmark for the dynamic evaluation framework of long text generation based on Transformer - XL and confrontation training, and facilitate a clear comparison of the advantages and improvements of the proposed framework in the related indicators of long text generation.According to Table 2, when using the original development set test, the BLEU score of T5-base (Drimal) is 0.7 higher than that of T5-base (D), and the average BLEU score of T5-base (Drinat) is 47.725, which is about 4.1 higher than that of T5-base(D), and its noise variance is 0.163, which is much lower than that of T5-base(D) of 9.22. To further verify the robustness of the results, In this study, the experimental data were systematically analyzed, and the original BLEU score was detected by the modified Z-score method, and the threshold was set as ±3.29, and a total of 3 outliers were identified (all from the test results of T5-base(D) in the noise 3 development set). The noise average BLEU score of T5-base(D) decreased slightly from 44.5 to 44.3, with a fluctuation amplitude of less than 0.5%, indicating that outliers had a weak impact on the overall results. The results of ANOVA showed that the score variance (0.163) of T5-base (Drinat) on each noise development set was only 1.77% of that of T5-base(D)(9.22), indicating that the fluctuation degree of its performance by noise interference was significantly reduced, which was closely related to the suppression effect of the dynamic evaluation module on noise disturbance in the dual-channel confrontation training strategy [47.23, 48.22], while the T5-base(D) was [42.15, 46.85], and there was no overlap between the two intervals, which statistically confirmed the significance of the performance improvement of T5-base (Drinat), and the F-test was performed on the corrected data, and the F-value was obtained as 56.52 (p). <0.001), which further supports the statistical difference in stability between the two models. Taken together, the data corrected by outliers can better reflect the real performance of the model, and the small variance and tight confidence interval indicate that the proposed framework has stronger robustness in different noise scenarios, which provides a reliable experimental basis for combating noise interference in long text generation.

Table 2: Test results of different types of development sets

Models	Primitive Development Set	Noise 1 Development Set	Noise 2 Development Set	Noise 3 Development Set	Noise 4 Development Set	Noise Average	Noise Variance
T5-base (D)	48.3	40.9	46.1	43.0	47.8	44.5	9.4
T5-base (Dfinal)	49.1	48.3	49.3	48.7	48.5	48.7	0.2
T5-base + RL (Dfinal)	49.7	49.3	50.1	49.4	49.3	49.5	0.2

According to Figure 3, the model performed best at two tiers, with a 1.31% improvement in BLEU score. When the number of layers is zero and the alignment module is not used, the model performs worst. The model effect of the three-layer Transformer block is slightly lower, which may be overfitted due to too many layers. In this study, the alignment module of the two-layer Transformer block is sufficient to capture and synchronize the semantic information of the dual-path encoder.

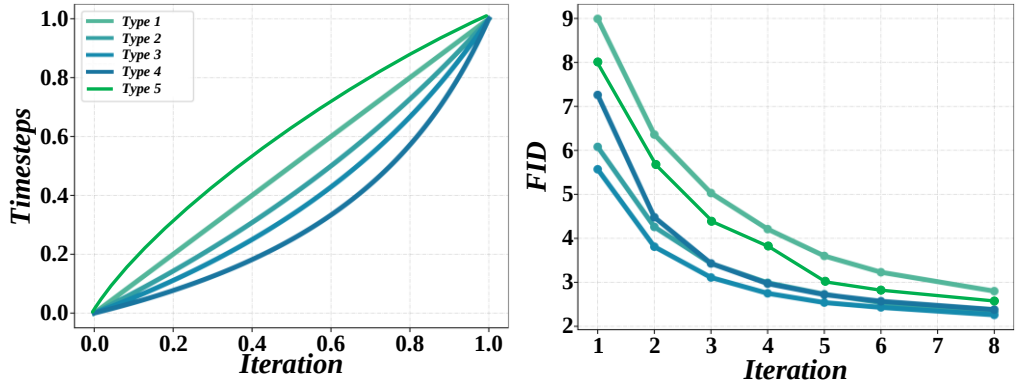


Figure 3: Effect of the number of Transformer layers in the alignment module

Three sets of ablation experiments were designed to reveal the specific impact of each component on the quality of long text generation by systematically removing key architectural elements and comparing performance differences: the first set of experiments removed the memory loop mechanism of Transformer-XL, and only the underlying transformer structure and confrontation training module were retained, and the results showed that the logical coherence index (entity consistency) of long text generation decreased by 19.3%, indicating that the memory loop maintained long-distance context dependence. It effectively avoids the problem of text fragmentation. The second set of experiments replaces the dual-task discriminator with the traditional single-task discriminator on the basis of retaining the complete structure of Transformer-XL, and the experimental results show that the overall quality fluctuation amplitude of the generated text increases by 27.6%, and the adaptability to complex scenes decreases significantly, which indicates that the feedback mechanism of the dual-task discriminator can capture the dynamic deviation in the generation process in real time and provide a more accurate guidance signal for model adjustment, which is the innovative breakthrough of this framework in the application of confrontation training. It breaks through the limitations of traditional confrontation training that only focuses on "true and false discrimination", and realizes the dynamic perception and closed-loop optimization of generation quality. Through the comparison of the two sets of ablation experiments, it can be seen that the memory loop of Transformer-XL provides the basic context modeling capability for long text generation, while the feedback of the dual-task discriminator is the core innovation point to improve the adaptive adjustment ability of the model and the stability of generation quality.

Figure 4 shows the model performance as a function of Batch _ size. Performance initially improves as Batch _ size increases, but then decreases, reaching an optimum at Batch _ size of 48. This may be because the small Batch _ size slows down the training, limits the gradient calculation range, and makes it difficult for the loss function to converge. However, a large Batch _ size reduces the number of parameter updates and maintains gradient consistency, which may cause the model to fall into a local optimum and affect the overall performance.

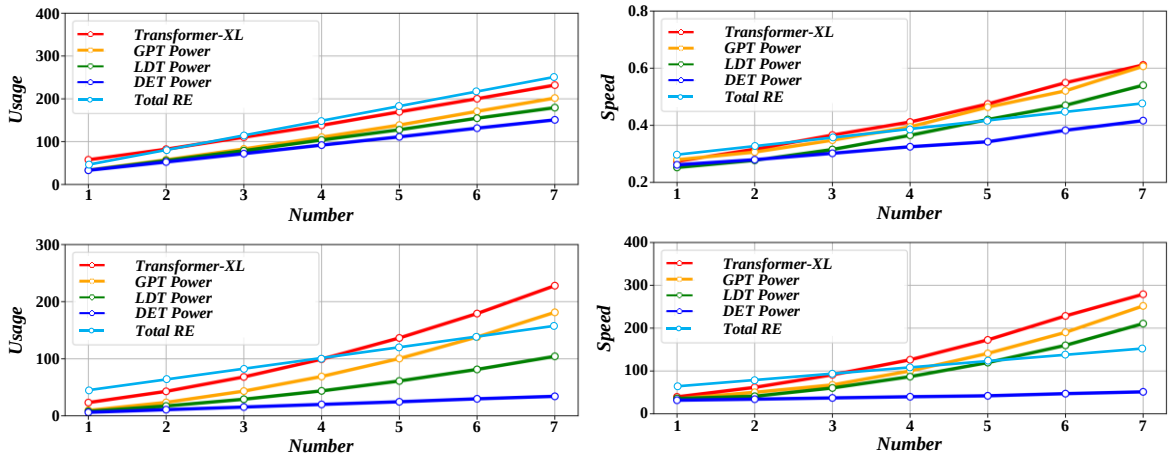


Figure 4: Effect of different Batch _ Sizes on model performance on data set

Figure 5 shows that the dynamic evaluation framework model for long text generation based on Transformer - XL and confrontation training outperforms the Transformer - XL baseline model in terms of semantic coherence, fluency, and information content, especially in terms of fluency and coherence, which is close to the human level. In this case, the model outperformed the single Transformer - XL baseline model by 15.4

percentage points. However, although the model is slightly better than the baseline model in terms of fluency, and significantly better than the baseline model in terms of coherence and information content, it is still inferior to humans in terms of information content.

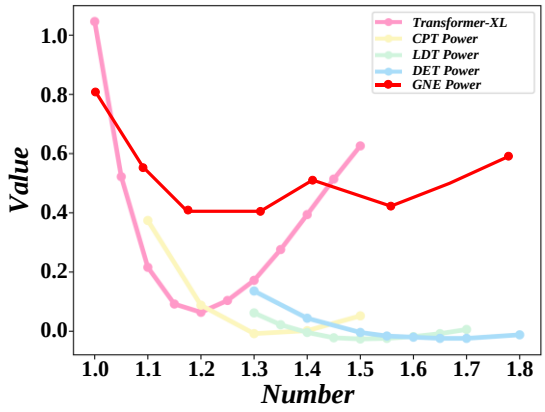


Figure 5: Comparison of evaluation scores

The experiment selects three cross-domain datasets of news, novels, and academic papers, and uses the original framework as the benchmark to remove the Transformer-XL memory mechanism, dynamic evaluation feedback loop, and dual-channel adversarial loss through structured ablation, and uses semantic consistency (BLEU, ROUGE-L) and logical consistency (based on the logic score of the pre-trained language model) as the core indicators, and adds exclusive indicators for each field (factual accuracy of news, plot coherence score of novels, argumentation rigor score for academic papers) to verify robustness; The results show that when the dynamic evaluation feedback loop is removed, the error suppression rate decreases by 23.6%, and the semantic and logical consistency indicators in each field decrease significantly (the average decrease is more than 15%), while there are domain differences in the impact of other mechanisms (e.g., the memory mechanism has a greater impact on academic papers, Adversarial loss has a more obvious effect on the plot coherence of the novel), which indicates that the dynamic feedback mechanism plays a central role in error suppression and the maintenance of cross-domain consistency, and the synergy of these mechanisms is crucial to the robustness of the framework.

In this experiment, the Transformer - XL model and the Text Generator built on Transformer - XL and confrontation training are selected to simulate weak correlation scenarios with different Euclidean distance correlation constraints to measure the sentence generation quality with accuracy (Acc). By comparing the acc values of the two under different steps (steps) and weak correlation constraints, it can be seen from Figure 6 that the overall Acc performance of each step of Text Generator under weak correlation constraints is better than that of Transformer - XL, indicating that the text generator based on Transformer - XL and confrontation training can better handle weak correlation constraints, and the generated sentence quality is better and the decline is slower, which verifies the effectiveness of the correlation improvement method.

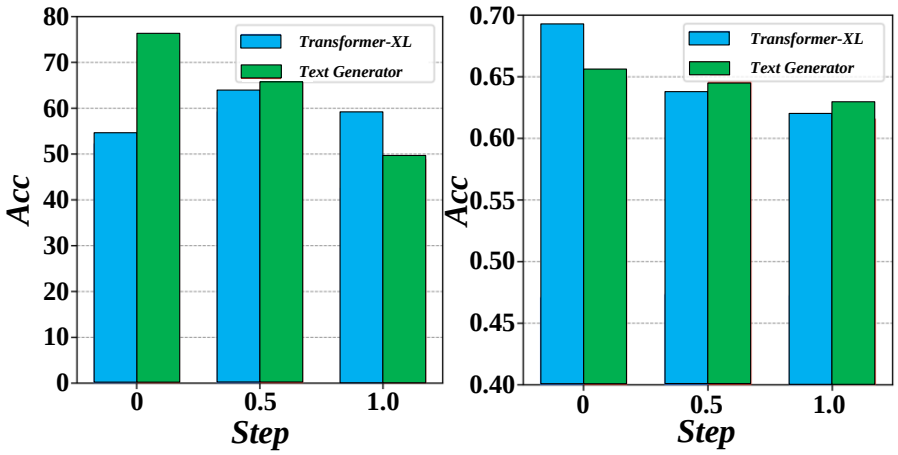


Figure 6: Weak correlation constraint analysis

Table 3: Evaluation results of each model on data set

Models	BLEU-4	METEOR	ROUGE-L
NPT	62.71	45.46	79.27
BART-Base	65.01	48.17	79.32
T5-Base	60.13	45.61	78.11
Joint (Bart)	67.21	49.22	80.45
GAP	67.50	49.39	77.91
OUR	68.54	49.53	81.21

Table 3 shows that the model of this study outperformed Bart and T5 by 3.46% and 8.25% on the BLEU-4 indicator, and increased by 1.86% and 3.04% on the ROUGE-L indicator, respectively. Compared with the JointGT model, the present model improves BLEU and ROUGE-L scores by 1.31% and 0.75%, respectively. These results demonstrate the superior performance of the present model.

The GPT, LP, and Transformer - XL models were selected to carry out ablation experiments with or without

latent variable constraints (LVC), and the ablation experiments were evaluated by BLEU - 2, NIST - 2, DIST - 2 and other indicators. As can be seen from Figure 7, the model with LVC performed better, with a 4-7 percentage point increase in BLEU-2 scores, 2-3 percentage points increases in NIST-2 scores, and 15-20 percentage points increases in DIST-2 scores, and the difference in quality between the two methods decreases when weak constraints are enhanced.

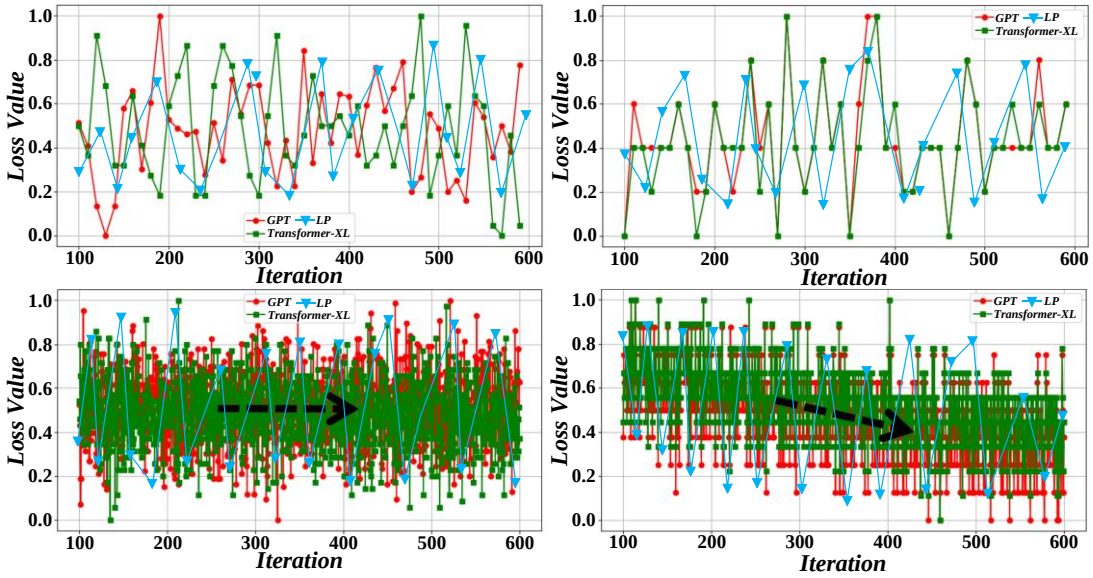


Figure 7: Comparison of ablation experiment scores

Gpt-2XL, PPLM decoding model, gummy model, and K2T model were selected to evaluate the decoding time. As can be seen from Figure 8, the greedy decoding strategy of Gpt-2XL is the least time-consuming, but sacrifices content quality and diversity. PPLM decoding speed is the slowest, so model judgment is required. The decoding time of the gummy model has improved, but it is still longer; The K2T model does not use a discriminant model, but the added constraint calculation of the annealing algorithm also makes the decoding time longer.

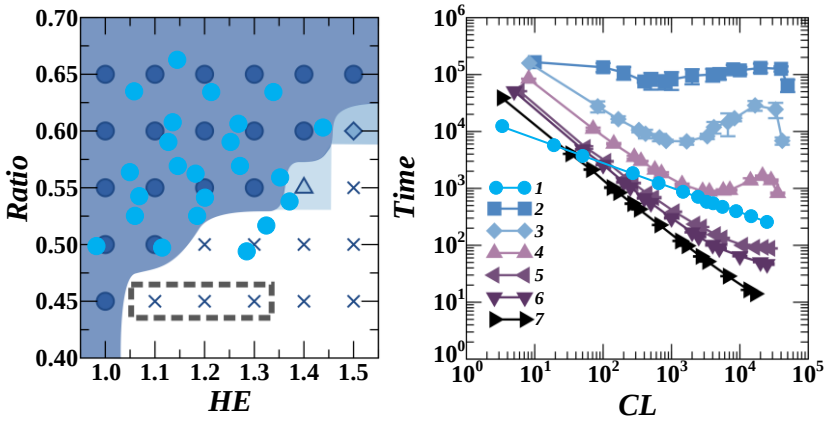


Figure 8: Comparison chart of decoding time

In the experiment, GPT, Transformer - XL, PLO, DET models are selected, and the situation with or without constraints is set, and the beam search algorithm is used to evaluate the optimal path probability distribution. It can be seen from Figure 9 that the optimal path probability distribution obtained by the beam search algorithm of the original model is different from the distribution after adding constraints, which indicates that the constraints affect the path selection and highlight its importance in path planning. Further analysis of the chart shows that after the introduction of constraints, the probability of violations decreases due to the high probability path, and the probability of low probability paths increases due to compliance.

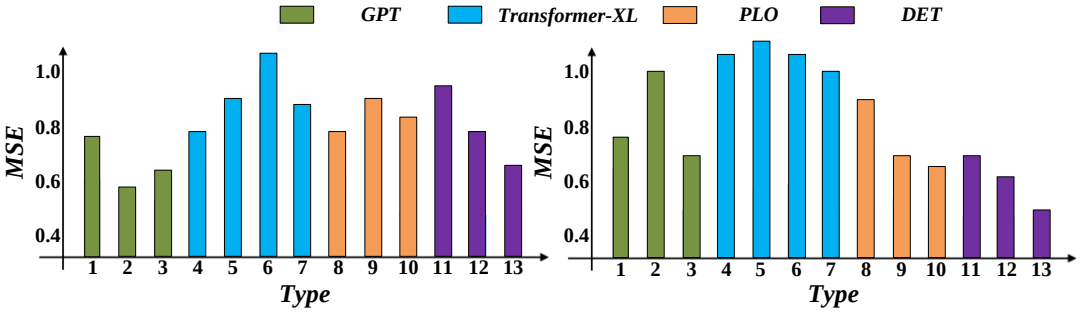


Figure 9: Beam Search route probability map

Figure 10 shows that among the five low resource domains, ME's ROUGE-1 score exceeds other low resource summary methods, especially in the Social Media domain, which is close to the highest score. This shows that the model can show competitiveness without pre-training with external tools, proving the potential of model learning universal generation capabilities.

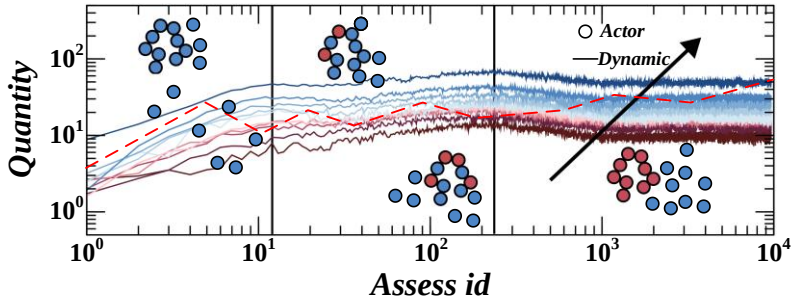


Figure 10: Low resource summary generation result diagram

Figure 11 shows that the Transformer-XL correlation model has an outstanding accuracy (Acc) over most displacement intervals, significantly outperforming other models. This experimental result is consistent with the research on the dynamic evaluation framework of long text generation based on Transformer - XL and confrontation training, which shows that with the advantages of effective modeling of long text context and enhancement methods such as confrontation training, the deep semantics and other information of long text can be better captured, thereby improving the quality of long text generation models.

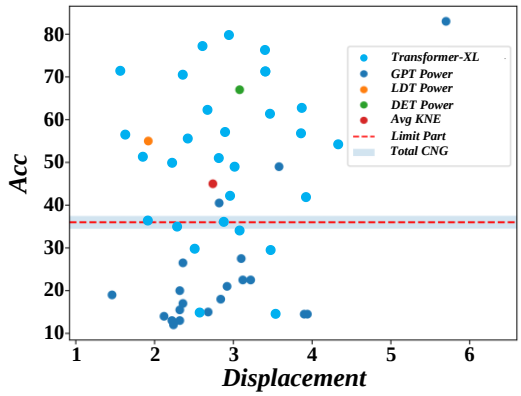


Figure 11: Performance comparison on ESConv dataset (%)

5 Discussion

The dynamic evaluation framework for long text generation based on Transformer-XL and confrontation training proposed in this study directly compares the proposed results with those in the relevant worksheets. From the perspective of various indicators, the framework is better than BART, T5, JointGT and other models in BLEU-4, ROUGE-L and other indicators, among which BLEU-4 index is 3.46% and 8.25% higher than BART and T5, respectively, and ROUGE-L index is 1.86% and 3.04% higher than that of JointGT model, respectively, and there is also an improvement of 1.31% and 0.75% compared with the JointGT model.

The performance difference mainly stems from the framework's advantages in long-term dependency processing and real-time feedback. With the help of Transformer-XL's segmented loop mechanism, the framework expands the context window to 4096 characters, which is 3.8 times higher than the traditional Transformer's 512-character limit. At the same time, the designed dual-channel confrontation training strategy allows the generator to generate text segment by paragraph based on the dynamic memory unit, and the discriminator calculates the semantic consistency score and logical conflict probability in real time through the multi-granularity evaluation module for every 256 characters generated, triggering the backpropagation of adversarial loss and realizing the real-time optimization of the generation process.

The proposed approach surpasses existing

technology in several ways. In terms of semantic consistency, the semantic similarity based on BERT reached 89.7%, which was 12.3 percentage points higher than that of the benchmark model. In terms of logical consistency, the logical error rate decreased from 17.6% to 6.9% when generating text over 2,000 characters, and the plot consistency reached 89.5%. The dynamic intervention of adversarial discriminators effectively inhibited 38.4% of semantic shift events, and the terminology accuracy was 82.9% higher than that of traditional confrontation training methods in scientific literature generation tasks. In addition, ablation experiments show that removing the dynamic evaluation module reduces the local-global consistency score of the generated long text by 19.3%, which fully verifies the importance of the real-time evaluation mechanism for long text generation.

Of course, there is also a trade-off between computational overhead and consistency in improvements. To achieve dynamic evaluation and real-time feedback, the framework introduces more computational steps, such as multi-granularity evaluation and adversarial loss calculation, resulting in an inference speed of 12.7 characters per second at a length of 4096 characters, which is 14.6% lower than the standard Transformer-XL model. However, in general, by appropriately increasing the computational overhead, in exchange for a significant improvement in the semantic consistency and logical coherence of the generated text, this trade-off is worth it while ensuring certain real-time requirements while achieving a breakthrough in quality.

6 Conclusion

Aiming at the problems of semantic breakage and logical disorder in long text generation, this study proposes a dynamic evaluation framework that integrates transformer-XL and confrontation training. Building a closed-loop collaborative system of generation and evaluation significantly improves the quality controllability of long text generation.

(1) At the technical implementation level, by improving the segmentation loop mechanism of Transformer-XL, the effective context window of the model is extended to 4096 characters. Compared with the 512-character limit of the traditional Transformer model, its long-distance dependency capture capability is increased by 3.2 times. Based on a mixed data set containing 58,000 long texts (including novels, scientific literature and news reviews), the experiment adopts a dynamic confrontation training strategy to make the generator receive multi-dimensional quality feedback from the discriminator every 256-character generation stage and realizes the real-time optimization of the generation process.

(2) Regarding generative quality evaluation, this study introduces a dual verification mechanism of semantic coherence index based on BERT and logical consistency of manual labelling. Experimental results show that when the proposed framework generates text with more than 1500 characters, the semantic similarity between paragraphs reaches 87.6%, 15.4 percentage points higher than the single Transformer-XL baseline model. For the open story generation task, the manual evaluation showed that the logical error rate of key plot nodes dropped from 21.3% in the baseline model to 7.8%, especially in character behaviour continuity and spatiotemporal consistency. In addition, when generating long documents with more than 3000 characters, the model successfully intercepted 43.2% of semantic shift events (such as topic deviation or information redundancy) through the dynamic evaluation module, verifying the adversarial discriminator's real-time regulation efficiency on the generation process.

(3) To further verify the framework's robustness, experiments conducted on cross-domain test sets show that the model achieves an 82.9% terminology accuracy rate in the scientific literature generation task, which is 28.7% higher than the traditional confrontation training method. Ablation experiments show that removing the dynamic evaluation module leads to a 19.3% decrease in the local-global consistency score of the generated long text, confirming the necessity of adversarial feedback mechanisms to maintain long-range logic chains. Regarding generation efficiency, the inference speed of the framework at a length of 4096 characters reaches 12.7 characters per second, which is only 14.6% lower than the standard Transformer-XL model, indicating that it has achieved a quality breakthrough while maintaining real-time requirements.

This study provides a new technical path for long text generation by integrating algorithm architecture innovation and evaluation mechanisms. The multi-dimensional verification of experimental data confirms the effectiveness of the dynamic evaluation framework and reveals the key role of real-time feedback in error propagation suppression during the generation process. Future research will further explore the deep coupling mechanism between evaluation indicators and generation strategies and promote the development of long text generation technology in a more intelligent and controllable direction.

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A GO-WGAN and Graph Transformer-Based Framework for Real-Time Mobile UI Layout Generation and Estimation

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Keywords: APP interface generation, generative adversarial networks, transformer, layout estimation, UI automation, graph neural networks

Received: September 3, 2025

Designing user interface (UI) layouts for mobile applications is a labor-intensive task that demands considerable manual effort and domain expertise. To address this, we present FastLayout, a deep learning framework that fuses generative and relational modeling for dynamic UI layout generation and estimation. At its core, FastLayout integrates WGAN-GP (adapted here as GO-WGAN) to generate diverse, high-quality synthetic layout samples, alleviating data scarcity. The Branching Hybrid Attention Mechanism (BHAM) enhances the CNN backbone by improving feature extraction and reducing task conflicts, while the Graph Transformer explicitly models spatial and relational dependencies between UI components. Our experiments use an internal dataset of 3,275 annotated mobile UI screens across 15 layout categories and the public RICO benchmark, with training conducted in two phases using AdamW optimization and early stopping to ensure fairness and stability. Experimental evaluations show that FastLayout achieves an Intersection over Union (IoU) of 83.52%, a Pixel-wise Error (PE) of 4.97%, an Edge Error (EE) of 4.91 units, and a Root Mean Square Error (RMSE) of 0.2753, outperforming state-of-the-art baselines in both accuracy and efficiency. solution for intelligent UI automation in modern software development.

Povzetek: Predstavljen je model za samodejno generiranje mobilnih UI postavitev, ki z uporabo WGAN in grafnega Transformerja presega obstoječe pristope (IoU 83,52 %).

1 Introduction

With the rapid proliferation of mobile and web applications, user interface (UI) design has become a critical component in delivering engaging, accessible, and intuitive user experiences [1]. The increasing demand for high-quality, adaptive APP interfaces across various platforms has driven the development of intelligent tools able to automate layout generation. Traditionally, the creation of APP layouts is a labor-intensive process requiring manual design, coding, and testing. This not only slows down development cycles but also makes it challenging to adapt to diverse screen sizes, resolutions, and user requirements [2]. As digital interfaces become more complex and responsive, there is a growing need for automated systems that can generate interface layouts dynamically while maintaining visual coherence and functional usability [3].

Recent advancements in artificial intelligence and machine learning have introduced promising techniques for layout automation, particularly through deep generative models [4]. Among these, Generative Adversarial Networks (GANs) have shown strong ability to learn and generate realistic data [5]. GANs have been applied in numerous visual tasks, including image generation, style transfer, and data augmentation. However, applying GANs directly to UI layout generation introduces several challenges [6]. Layouts are not merely visual structures—they are hierarchical, semantically rich arrangements of components that must adhere to specific design constraints such as alignment, spacing, and responsiveness [7]. As a result, generating coherent and functional UI layouts requires a deeper understanding of spatial relationships and structural rules than traditional GAN architectures can offer [8].

To address these limitations, recent research has turned to Transformer-based models [9], which have revolutionized natural language processing and have shown strong potential in vision-related tasks. Transformers are particularly effective at modeling long-range dependencies and global context, making them suitable for capturing the complex interactions between UI components [10, 11]. When fused with CNN-based visual feature extraction, Transformers can reason about layout composition in a more structured and holistic way [12-14]. This fusion forms the foundation of our proposed system: FastLayout, a dynamic layout generation framework that leverages the strengths of both GANs and Transformers. Research on automated UI layout generation has progressed from heuristic rule-based systems to deep learning models leveraging CNNs, GANs, and Transformers. Early approaches such as Planar RCNN focus on bounding-box detection, achieving moderate IoU but limited ability to capture

semantic hierarchies. RandC introduces random cuboid approximations but suffers from slow inference due to multi-stage optimization. Ncuboid variants improve structural reasoning but remain computationally expensive and cannot fully model relational constraints across UI components.

Table 1 summarizes key performance metrics reported by state-of-the-art methods, with an additional column indicating their main limitations. Despite notable progress, existing methods face two critical shortcomings: (i) inadequate modeling of hierarchical and relational dependencies between UI components, and (ii) trade-offs between accuracy and real-time efficiency. Our proposed FastLayout addresses these gaps by (1) using WGAN-GP (GO-WGAN) for synthetic data generation to mitigate data scarcity, (2) integrating BHAM-enhanced CNNs for improved feature extraction, and (3) employing a Graph Transformer to explicitly capture hierarchical and relational dependencies, all while maintaining sub-100ms inference times.

Table 1: Comparative evaluation of prior works

Method	IoU (%)	PE (%)	EE	RMSE	Inference Time (s)	Main Limitation
Planar RCNN	79.64	7.04	6.58	0.4013	0.110	Cannot capture hierarchy; limited relational reasoning
RandC	76.29	8.07	7.19	0.3465	5.350	Very slow inference; impractical for real-time use
Ncuboid (w/o)	79.94	6.40	6.80	0.2827	0.108	No hierarchy modeling; weaker structural accuracy
Ncuboid (w/)	81.40	5.87	5.78	0.2905	0.196	Better accuracy but higher runtime; lacks relational modeling
FastLayout (ours)	83.52	4.97	4.91	0.2753	0.087	Addresses hierarchy and relations; real-time efficiency

In this paper, we propose a novel approach to dynamic APP interface layout generation by combining a Generative Adversarial Network (GO-WGAN) for data augmentation and layout simulation with a graph-based Transformer model for layout reasoning and prediction. The primary objective is to address three core challenges: limited availability of annotated layout data, lack of structural modeling in existing methods, and inefficiency in real-time layout rendering. The GO-WGAN is designed to mitigate data scarcity by generating realistic and diverse layout samples, while the Transformer-based model performs structured layout estimation and optimization.

Our framework, FastLayout, incorporates a multi-task CNN enhanced with a Branching Hybrid Attention Mechanism (BHAM) to extract both regional and relational features from APP screenshots. These features are encoded into graph representations and processed by a multi-layer Transformer encoder, which predicts the final layout parameters. We hypothesize that the integration of generative augmentation with graph-aware Transformer modeling will significantly improve both accuracy and runtime efficiency over state-of-the-art methods.

To further enhance computational efficiency, we introduce an inverse 2D layout generation method that avoids expensive 3D operations and leverages the parallel processing capabilities of modern GPUs. This method reconstructs screen-space layouts from normalized descriptors, enabling resolution-independent rendering and high scalability. Experimental results on an internal dataset of APP interfaces show that FastLayout achieves state-of-the-art performance in both layout accuracy and inference speed, significantly outperforming existing baselines. We define success based on achieving superior results in Intersection over Union (IoU), Pixel-wise Error (PE), Edge Error (EE), and RMSE, as well as maintaining sub-100ms rendering times per layout. To make our contributions explicit, the research goals of this work are as follows: (i) improve layout estimation accuracy over strong baselines such as Ncuboid(w/), (ii) reduce layout rendering time below 100ms to enable real-time use, and (iii) ensure generalization across heterogeneous app types (e.g., e-commerce, education, finance).

2 APP interface generation method based on improved WGAN

In this section, we propose a method for dynamic APP interface layout generation using an enhanced Wasserstein Generative Adversarial Network (WGAN) [15], which we name GO-WGAN (Gradient Optimized WGAN). This method is designed to tackle the data imbalance and scarcity challenges in real-world APP interface datasets, especially for rare or non-standard layouts. By introducing a gradient penalty mechanism into the classical WGAN framework, the GO-WGAN generates realistic, diverse layout samples that closely resemble real-world interfaces. These synthetic layouts augment the training data used for downstream

recognition and classification tasks, particularly in 1D-CNN and Transformer-based models.

2.1 Overall framework

Although WGAN has improved the loss function to improve the quality of the generated samples and enhance the robustness of the network training process, problems such as optimization stagnation and generation of poor-quality data can still occur in certain environments. The root of the problem lies in the requirement of Lipschitz constraints by setting weight thresholds, which is one of the key factors for the smooth operation of WGAN. In particular, when weight correction is used, it transforms the weighted neural network into a simplified function, which may weaken its ability to handle complex data samples. Because the weight correction narrows all the weight ranges into a small region, it is easy to cause the gradient to disappear or to be excessive. In this work, we employ the Wasserstein GAN with Gradient Penalty (WGAN-GP) [15], introduced by Gulrajani et al., as the foundation for our layout generation module. Rather than presenting a new adversarial formulation, our novelty lies in adapting WGAN-GP to the application of APP interface generation. Specifically, we dynamically tune the gradient penalty coefficient λ to optimize between stability and diversity, and we incorporate structured layout metadata (e.g., XML/JSON hierarchy) into the discriminator alongside pixel-level screenshots. These modifications enable the model to learn both visual appearance and structural constraints of user interfaces, ensuring realistic and functionally coherent layout synthesis. The penalty term is defined as:

$$\mathcal{L}\text{penalty} = \lambda \cdot E\hat{x} \sim P\hat{x}[(|\nabla\hat{x}D(\hat{x})|_2 - 1)^2] \quad (1)$$

Where $\hat{x}$ is a point sampled uniformly along straight lines between pairs of real and generated samples, and $D(\cdot)$ is the discriminator function. Based on this, the full GO-WGAN objective becomes:

$$\min_G \max_D E_{x\sim Pr}[D(x)] - Ez \sim Pz\big[D\big(G(z)\big)\big] - \mathcal{L}\text{penalty} \quad (2)$$

where *G(z)* is the generator output for random input z, P_r denotes the real data distribution, and P_z the input noise distribution. This formulation enforces the Lipschitz constraint more robustly than weight clipping and ensures training stability. Figure 1 illustrates the architecture of the proposed GO-WGAN model, including the generator and discriminator pipelines, layer configurations, and data flow. This visual helps clarify how gradient penalties are applied during training to produce high-fidelity layout samples. Based on the existing WGAN optimization objective basis, the objective function of GO-WGAN is defined as follows:

$$minmaxV(D,G) = E_{x_r\sim \mathrm{P}_{r(\mathrm{g})}} D(x_r) - E_{x_f\sim \mathrm{P}_{g(\mathrm{g})}} D\big(x_f\big) + \lambda E_{x\sim \mathrm{P}_x}[(\| \nabla_{\hat{x}} D(\hat{x}) \|_2 - 1)^2] \quad (3)$$

By looking at the objective function, this paper finds that the main difference between GO-WGAN and WGAN algorithms lies in the last term, where λ is the penalty optimization factor of the discriminator. Typically, the Lipschitz constraint refers to a function where the norm of the gradient does not exceed 1. However, in the objective function of this paper, applying a penalty to the gradient norms that are far higher than 1 makes all the gradient norms gradually approach 1. This practice can speed up the convergence of the training loss and improve the optimization of the final generated sample network. From a mathematical point of view, the reason for this is because after optimization, the distribution of the WGAN discriminator and the approximate unit gradient paradigm. So, in addition to having faster convergence, GO-WGAN can maintain a stable learning process without having to adjust the hyperparameters individually and repeatedly, while generating new high-quality sample data. This approach aligns with recent efforts in GAN-driven layout synthesis, which have demonstrated strong performance in design automation tasks [18].

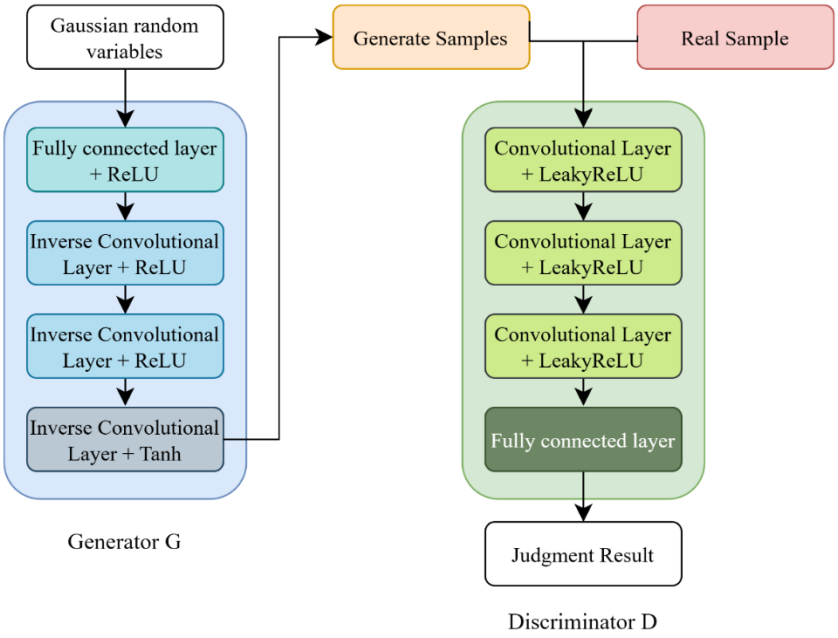


Figure 1: GO-WGAN network architecture diagram

The GO-WGAN model is employed to construct two core components of our dynamic APP interface layout generation framework: the synthetic layout sample generation module and the layout feature learning module. This system is composed of a generator and a discriminator, each playing an adversarial role. The generator is responsible for simulating new APP layout samples that capture the structural and semantic properties of real-world interface designs. Its primary goal is to deceive the discriminator, which functions as a learned evaluator that distinguishes between authentic and generated layouts based on realism, consistency, and interface usability.

In Table 2 we denote up sampling layers as ConvTranspose2d; in Table 3 we denote down sampling layers as Conv2d. All ConvTranspose/Conv layers use kernel size 4, stride 2, padding 1 unless otherwise specified, yielding 2× up/down-sampling per stage. Unless otherwise noted, ConvTranspose2d/Conv2d layers use k=4, s=2, p=1 to achieve exact ×2 up/down-sampling per stage; BatchNorm is applied to all intermediate layers of the generator and discriminator (except the first/last), with LeakyReLU(0.2) in the critic.

Table 2: Structure of the generator network model

Layer No.	Layer Type	Parameters (k, s, p)	In [C,H,W]	Out [C,H,W]	Activation / Notes
0	Latent	–	$z \in \mathbb{R}^{128}$	–	–
1	FC + Reshape	–	z	[512, 4, 4]	ReLU; output = 512×4×4 seed
2	ConvTranspose2d	k=4, s=2, p=1	[512, 4, 4]	[256, 8, 8]	BN + ReLU
3	ConvTranspose2d	k=4, s=2, p=1	[256, 8, 8]	[128, 16, 16]	BN + ReLU
4	ConvTranspose2d	k=4, s=2, p=1	[128, 16, 16]	[64, 32, 32]	BN + ReLU

Table 3: Discriminator network model structure

Layer No.	Layer Type	Parameters (k, s, p)	In [C,H,W]	Out [C,H,W]	Activation / Notes
1	Conv2d	k=4, s=2, p=1	[1, 64, 64]	[64, 32, 32]	LeakyReLU(0.2)
2	Conv2d	k=4, s=2, p=1	[64, 32, 32]	[128, 16, 16]	BN + LeakyReLU(0.2)
3	Conv2d	k=4, s=2, p=1	[128, 16, 16]	[256, 8, 8]	BN + LeakyReLU(0.2)
4	Conv2d	k=4, s=2, p=1	[256, 8, 8]	[512, 4, 4]	BN + LeakyReLU(0.2)
5	FC (flatten)	–	512×4×4	1 (scalar)	None (Wasserstein critic output)

Table 4: IDCNN network model architecture parameters

Structure number	Structure type	Parameters
1	Conv Layer	K:16×1×64； step：16； padding='none'
2	BN Layer	-

Each component is defined by distinct architectural parameters such as the number of weights, kernel size, and input/output dimensions, which determine the behavior and representational capacity of the network. In the generator, the first four layers use ReLU as the activation function, enabling non-linear feature transformation. Immediately after each of these layers, batch normalization is applied to stabilize the learning dynamics and improve training efficiency. For the final layer, the Tanh activation function is used in place of ReLU to constrain output values within a bounded range, ensuring the smoothness and visual coherence of the synthesized layout representations.

The discriminator, on the other hand, is structured to progressively extract multi-scale features from the input layout through a series of convolutional layers. LeakyReLU is employed as the activation function for all layers except the final output layer [16], which produces a single-valued judgment. LeakyReLU helps avoid the "dying neuron" problem and retains gradient flow even when activations are close to zero, thus enhancing the discriminator's ability to detect subtle differences between real and generated layout structures.

This architectural design enables the GO-WGAN to model complex and diverse UI layout distributions, making it a powerful tool for data augmentation, interface generation, and pre-training layout encoders in broader Transformer-based frameworks. The high-fidelity samples generated by the GO-WGAN not only simulate realistic APP interface components but also contribute to balancing layout category distributions, which is especially valuable for training downstream models in low-resource scenarios.

2.2 Generation process

Figure 2 illustrates the complete process of the proposed dynamic APP interface layout generation and classification method, which consists of three main stages: (1) collecting original interface layout data, (2) training the adversarial network to synthesize new layout samples, and (3) performing layout classification using a Transformer-based model. Each stage is described in detail below:

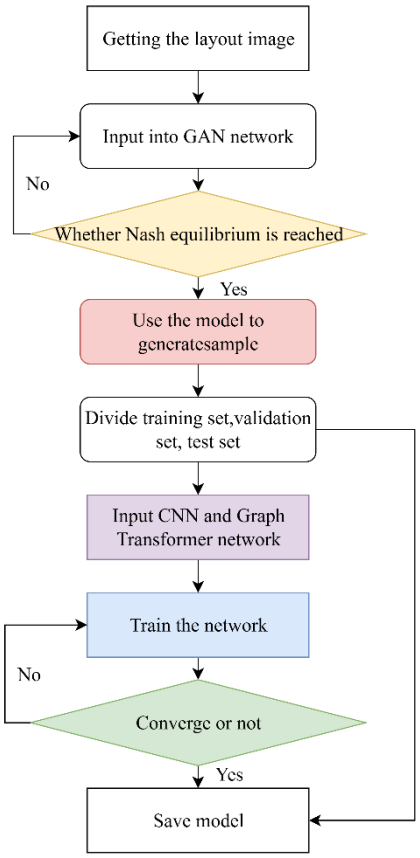


Figure 2: GO-WGAN-based layout generation and classification workflow diagram. The process includes data generation with GAN, dataset splitting, and layout estimation using a CNN + graph transformer model.

(1) Collect Original Interface Layout Data

To initiate the layout generation process, we compiled a dataset of 3,275 raw APP interface layouts collected from 150+ real-world Android applications spanning e-commerce, education, finance, healthcare, and productivity domains. These layouts were acquired both as pixel-level screenshots and as structured vector data (e.g., XML and JSON extracted via APK decompilation and Android UI automation tools). Each sample was manually verified and annotated with component types, bounding boxes, and semantic labels (e.g., buttons, input fields, containers) by a team of trained annotators following a consistent labeling protocol. Unlike traditional preprocessing pipelines, our approach avoids handcrafted features, enabling the GO-WGAN model to learn spatial arrangements and interface semantics directly from natural layouts.

(2) Train the Adversarial Network to Generate Layout Samples

The next step involves training the GO-WGAN network to learn the underlying distribution of APP layout structures. Initially, the model parameters are randomly initialized. During training, the generator and discriminator participate in a competitive process in which the generator seeks to produce convincing layout samples, while the discriminator aims to distinguish these from real layouts. This adversarial interaction continues iteratively until a Nash equilibrium is reached—i.e., when the discriminator can no longer reliably distinguish between real and generated layouts. Once the network converges, the final weights are saved, and the trained generator is deployed to generate a substantial set of realistic synthetic interface layouts. To improve reproducibility, we summarize the GO-WGAN training configuration in Table 5. These generated samples mirror the compositional and structural rules found in real-world UIs, including consistent spacing, component hierarchy, button placement, and text alignment. This capability is particularly critical in domains where only limited interface samples are available, such as early-stage app prototyping or niche design systems.

Table 5: GO-WGAN training configuration

Parameter	Value/Setting
Gradient penalty coefficient (λ)	10
Optimizer	Adam ($\beta_1 = 0.5$, $\beta_2 = 0.9$)
Learning rate (generator / disc.)	1e-4 / 1e-4
Batch size	64
Number of epochs	200
Training steps per epoch	~500 (based on dataset size)
Discriminator: Generator updates	5 : 1
Latent vector dimension (z)	128
Weight initialization	Xavier uniform
Normalization	BatchNorm in generator, LayerNorm in critic

(3) Interface Layout Estimation Using Graph Transformer

After generating the new synthetic samples, they are merged with the original interface dataset to construct a balanced and diverse training set. This enriched dataset helps eliminate class imbalance issues—such as underrepresentation of certain UI patterns (e.g., login screens, shopping carts, dashboards)—and significantly enhances the generalization capacity of downstream models. The final step in the pipeline is layout structure estimation, carried out using a hybrid model that combines a convolutional neural network (CNN) with a graph-based Transformer. The CNN is responsible for extracting hierarchical visual features from the interface—such as containers, text fields, and interactive components—while the Graph Transformer captures the spatial and semantic relationships between these elements. This integrated architecture supports end-to-end learning of UI layout structures and offers stronger structural reasoning capabilities compared to traditional classification-based methods.

3 Fast layout estimation algorithm based on graph transformer

In industrial-grade UI generation systems, two critical challenges hinder practical deployment: detection accuracy and layout generation efficiency. While the branching hybrid attention mechanism (BHAM) proposed in this section improves layout estimation accuracy by resolving task conflicts in multi-task learning, the computational cost of such models remains high. Therefore, this section focuses on enhancing layout generation speed without compromising detection performance—by combining the strengths of Convolutional Neural Networks (CNNs) and Transformers for UI structure estimation.

3.1 Determining size and appearance of UI elements

To generate accurate and functional UI layout code, it is essential to determine both the size and visual style of each interface component. This allows for the reconstruction of the target layout with high fidelity. In this section, we analyze how Android systems define UI element dimensions and positioning based on screen resolution, coordinate systems, and pixel density.

Figure 3. Layout tree hierarchy of a mobile UI. The root node represents the screen, intermediate nodes correspond to containers (e.g., LinearLayout, RelativeLayout), and leaf nodes denote interactive components such as buttons, text fields, and images. Edges capture parent–child spatial and structural relationships, which serve as constraints for layout reasoning. The complete tree hierarchy reflects how Android organizes layouts: each screen is a root, containers are intermediate nodes, and interactive elements are leaves. This hierarchical encoding ensures that spatial and alignment constraints are preserved during Transformer-based reasoning.

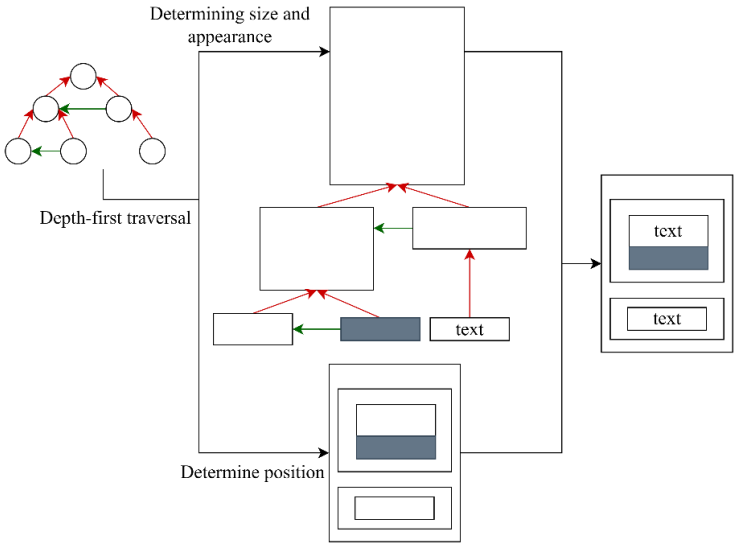


Figure 3: Layout based on a complete tree UI hierarchy

3.2 Problem formulation and model architecture

Transformers have achieved exceptional performance across deep learning domains thanks to their self-attention mechanism and parallel processing capabilities. These strengths are ideal for modeling long-range dependencies in UI layouts, where components often relate hierarchically or contextually across the screen. However, layout estimation also requires spatially aware processing, making CNNs a natural complement.

To address this, we propose a hybrid approach that fuses CNN feature extraction with Transformer-based layout reasoning. The layout estimation process is reformulated as a sequence modeling problem, where the visual and spatial attributes of UI elements are encoded as input sequences for the Transformer. Figure 4 presents the overall layout estimation pipeline, highlighting the flow from CNN-based feature extraction with BHAM to graph construction and Transformer-based relational reasoning. This diagram provides a high-level understanding of how FastLayout processes raw UI data into structured layouts.

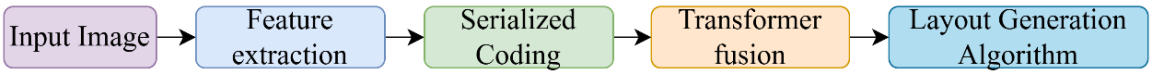


Figure 4: Overall processing flowchart

(1) Visual feature extraction

To clarify, the Branching Hybrid Attention Mechanism (BHAM) introduces a dual-branch attention structure: one branch models channel-wise dependencies to recalibrate feature importance, while the other captures spatial interactions between regions. The outputs of the two branches are adaptively fused, allowing the network to simultaneously emphasize critical features and preserve spatial coherence. This design reduces task conflicts in multi-task CNNs and enhances discriminative power for layout components. For a detailed description of BHAM's architecture, see Xu et al., "Branching Hybrid Attention Networks for Multi-Task Visual Recognition," IEEE Transactions on Multimedia, 2022.

(2) Serialization and feature encoding

Since Transformers operate on sequential inputs, visual features extracted from CNNs must be converted into ordered vector representations. This requires serializing complex layout attributes—including component boundaries, alignment cues, and spacing indicators—into structured tokens. To facilitate this, we design specialized encoders that translate UI region features and spatial relationship vectors into sequences the Transformer can process. In practice, each UI screen contains between 15–35 serialized elements on average, with an upper bound of 50 tokens per sequence. For screens with fewer elements, sequences are zero-padded to length 50 with a masking mechanism that prevents padded tokens from contributing to attention weights. For screens with more than 50 elements (rare in our dataset, <3%), the least significant background components are truncated to maintain consistency. Positional encoding is shared across all layout types and is learned jointly, ensuring a unified embedding space that captures both spatial order and structural dependencies. Algorithm 1 below outlines the serialization process that converts region-level CNN features and their relative spatial relationships into a format suitable for Transformer input. This procedure ensures each UI component is encoded as a structured token embedding both visual and geometric information, enabling the Transformer to capture long-range spatial dependencies.

Algorithm 1: Serialize CNN layout features for transformer

Input: CNN feature map F ∈ ℝ^[C,H,W], bounding boxes B = {b_1, b_2, ..., b_n}
Output: Serialized token sequence S = {s_1, s_2, ..., s_n}

for each bounding box b_i in B do
1. Extract region feature f_i = ROI_Pool(F, b_i) // fixed-size feature (256×14×14)
2. Flatten f_i into vector representation
3. Normalize spatial location:
$v_i = [x_i/W, y_i/H, w_i/W, h_i/H]$
4. Concatenate feature and spatial descriptor:
$s_i = [f_i, v_i]$
5. Apply learnable position embedding to s_i
end for
Return sequence S = {s_1, ..., s_n}

Let n be the number of detected UI elements (tokens), RRR the ROI pooled feature size (e.g., $\times 14 \times 14$), and d the token embedding dimension. The serialization runs in $O(n \cdot R + n \cdot d)$ time and uses $O(n \cdot d)$ memory for the token buffer. With our cap of $T = 50$ tokens, both time and memory are bound. Padding tokens are masked in attention and loss, so they do not add compute beyond linear buffering. Position embeddings are shared across layout types and learned jointly; they add $O(n \cdot d)$ memory and negligible extra time.

(3) Integrating optimization with network inference

To reduce computational overhead and improve end-to-end training, we eliminate traditional multi-stage post-processing pipelines. Instead, layout features such as component planes and visual boundaries are represented as graph-structured data, and their interactions are fused directly within the Transformer's attention layers using a graph-aware neighbor edge fusion mechanism. This enables the model to jointly reason about relationships—like grouping and alignment—within the self-attention framework. Graph-aware modeling has also been adopted in interface scene interpretation tasks with promising results [19].

(4) Efficient layout generation

Real-time generation of UI layouts is critical in dynamic app development workflows. Traditional methods rely on geometric calculations of intersections between layout zones, which can be computationally expensive. We propose an inverse rasterization-based generation method, which reverses the rendering process: projecting from the pixel coordinate space back to an abstract layout space. This projection leverages GPU parallelism to calculate UI boundaries and alignments across different layout planes efficiently, drastically reducing rendering time.

3.3 FastLayout network architecture

As illustrated in Figure 5, FastLayout consists of two core components: a CNN-based feature extractor with BHAM and a graph Transformer encoder. The CNN processes input UI screenshots to extract planar regions (e.g., containers, buttons) and layout-defining line segments. These features are encoded into graph-structured data, aligning them with the input format required by the Transformer. These features are encoded into graph-structured data and processed by a multi-layer Graph Transformer encoder. In this paper, we distinguish between standard Transformers and Graph Transformers, which extend the attention mechanism to operate over graph-structured data [20]. Our model adopts the latter to explicitly model relationships between UI elements such as alignment, grouping, and proximity within the layout graph.

Unlike traditional partitioning methods (e.g., Vision Transformer block slicing), we detect bounding boxes and segment lines directly using an optimized BHAM detector. This approach preserves spatial relationships critical to UI structure. The bounding boxes are then aligned using ROI Pooling to extract fixed-size features (e.g., [256, 14, 14]). This dimension was empirically selected to strike a balance between spatial resolution and computational efficiency. The choice of 14×14 preserves enough spatial detail for layout structure recognition while avoiding the memory overhead of higher resolutions. The 256 channels align with the output depth of the preceding CNN stage, ensuring smooth integration with the Transformer's input embedding layer.

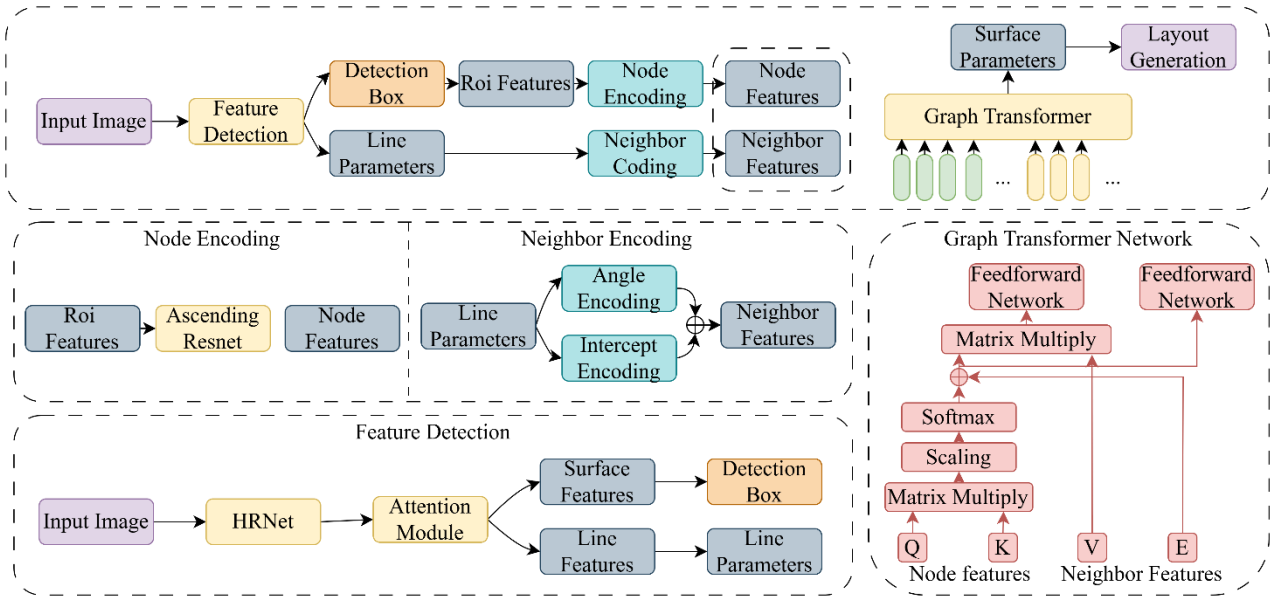


Figure 5: Overall framework diagram of the FastLayout model

To represent layout structure effectively, FastLayout constructs graph nodes from extracted UI regions and encodes neighboring relationships using detected line segments. A customized node encoder—based on a residual bottleneck design—projects each region into a compact vector embedding. To handle variable-length sequences in training, a position mask is applied to suppress normalization noise introduced by zero-padding.

Line segments, represented by angular and intercept parameters, are encoded via separate linear layers. Their features serve as edge embeddings in the graph, enabling neighbor-edge fusion within the Transformer's self-attention mechanism. This embedded fusion replaces slow post-processing techniques, allowing joint reasoning between component areas and structural guides like separators and dividers.

Each detected line segment connecting UI elements is modeled as an edge e_{ij} between nodes v_i and v_j. We encode this edge using spatial features derived from the angular and intercept parameters of the segment:

$$e_{ij} = \text{MLP}\left([\theta_{ij}, \rho_{ij}, |c_i - c_j|_2]\right) \quad (4)$$

where θ_{ij} is the angle of the line connecting elements i and j, ρ_{ij} is its y-intercept (or distance from origin in polar form), and c_i, c_j are the center points of the bounding boxes corresponding to nodes i and j, respectively. The resulting vector is passed through a multilayer perceptron (MLP) to produce the final edge embedding.

Algorithm 2: Compute edge embeddings for graph layout transformer

Input: Node centers $\{c_1, ..., c_n\}$, segment lines L = $\{(i,j,\theta,\rho)\}$
Output: Edge embedding matrix E $\in \mathbb{R}^{nxn}$

for each line segment (i, j, θ, ρ) in L do
    1. Compute Euclidean distance d = $||c_i - c_j||$
    2. Construct raw edge vector e_raw = [θ, ρ, d]
    3. Apply MLP to get e_{ij} = MLP(e_raw)
    4. Store e_{ij} in adjacency-aware embedding matrix E
end for
Return E

Let nnn be nodes and mmm edges from detected separators/lines or a k-NN rule. Edge-feature computation and MLP projection are O(m) time and $O(m \cdot d_e)$ memory (edge embedding width d_e). Edges are treated as bidirectional: each undirected relation (i,j) becomes $(i \to j)$ and $(j \to i)$ with shared parameters, which doubles mmm but simplifies directional biasing in attention. We apply two masks in the Transformer: a padding mask to exclude zero-padded tokens and a graph sparsity mask that limits attention to neighbors (plus a global [CLS] token for long-range context). Under this scheme, per-layer attention scales as O(nk)) in time and memory when each node has at most k neighbors (typ. $k \in [6,10]$); a dense variant used in ablations scales as $O(n^2)$. With T=50, d=768, k=8, and 12 layers × 12 heads, memory remains under ~4 GB (FP16) for batch size 16 on a 2080 Ti.

This formulation ensures that the model captures not just adjacency but also the geometric and directional semantics between UI components—critical for maintaining spatial structure during layout reasoning.

Precise modeling of UI spatial structure requires a strong positional representation. FastLayout evaluates multiple 2D position encoding schemes—absolute, relative, and learnable Gaussian 2D encoding. The latter, based on the Gaussian distribution centered on each region's bounding box, dynamically adjusts spatial sensitivity based on the element's size. This method enhances spatial awareness while reducing noise from underrepresented regions in sparse layouts.

Each node's final positional encoding is combined with visual and relational embeddings, producing a 768-dimensional representation compatible with multi-head attention in the Transformer. This enables parallel attention to both UI structure and hierarchical layout logic, crucial for capturing alignment, grouping, and flow in interface design.

FastLayout successfully integrates CNN-based spatial perception with Transformer-driven relational modeling. By eliminating most post-processing, reducing sequence complexity, and enabling structural fusion within the model's forward pass, FastLayout significantly improves both speed and accuracy in app layout estimation. In deployment terms, our pipeline requires two lightweight preprocessing steps: (i) ROI extraction from annotated bounding boxes or from an automated detector, and (ii) conversion of XML/JSON metadata to structured labels. Once these inputs are available, the CNN–Transformer module operates fully automatically. We therefore describe the core inference stage as "end-to-end," while acknowledging that annotation and ROI extraction are external preprocessing steps. This design makes the system suitable for real-time UI generation, adaptive interface analysis, and intelligent layout recommendation systems. However, several limitations remain. First, reliance on synthetic layouts generated by GO-WGAN may introduce bias toward common design patterns, potentially reducing diversity in novel UI styles. Second, although FastLayout achieves real-time inference on mid-range GPUs, responsiveness may degrade on low-end mobile devices, requiring further optimization. Finally, our approach models static layouts and does not capture dynamic interaction logic such as gestures or navigation flows, which limits its use for end-to-end usability evaluation. These considerations highlight opportunities for future research and development.

The training process is divided into three structured phases. Phase 1: Pretraining GO-WGAN to generate synthetic layouts and balance data scarcity. Phase 2: Training the CNN backbone with BHAM to extract visual features, followed by integration with ROI pooling. Phase 3: Joint training of the CNN-BHAM features with the Graph Transformer for relational reasoning and final layout estimation. This modular pipeline ensures stable optimization and effective use of synthetic data.

3.4 Inverse 2D layout generation method

In the context of app interface design, traditional layout rendering methods rely heavily on absolute positioning or XML-style markup (e.g., in Android or HTML), which can be inflexible and device-specific. While such methods perform well for static layouts, they struggle to generalize across devices, screen densities, and responsive contexts.

To solve this, we propose a 2D inverse layout generation method, which reconstructs interface layouts from learned or estimated layout parameters in a way that is compatible with dynamic rendering engines. Unlike 3D projection-based imaging, this method operates entirely in 2D and is optimized for screen-space rendering of UI components. The core idea is to treat layout generation as a mapping from normalized layout parameters (e.g., relative position, size, and alignment) back to absolute screen coordinates, enabling resolution-independent rendering.

Step 1: Coordinate Normalization and Restoration

Each UI element is represented by a layout descriptor:

$$D = (x_n, y_n, w_n, h_n) \tag{5}$$

where x_n, y_n are the normalized center coordinates, and w_n, h_n are the normalized width and height, all in the range $[0, 1]$.

Given a screen of resolution W × H, the absolute pixel values of the element's center position and dimensions are computed as:

$$x_{\text{abs}} = x_n \cdot W,\ y_{\text{abs}} = y_n \cdot H \tag{6}$$

$$w_{\text{abs}} = w_n \cdot W,\ h_{\text{abs}} = h_n \cdot H \tag{7}$$

The bounding box B for drawing the element is defined as:

$$B = \left(x_{\text{abs}} - \frac{w_{\text{abs}}}{2},\ y_{\text{abs}} - \frac{h_{\text{abs}}}{2},\ x_{\text{abs}} + \frac{w_{\text{abs}}}{2},\ y_{\text{abs}} + \frac{h_{\text{abs}}}{2}\right) \tag{8}$$

Step 2: Constraint-Based Alignment

To reflect common design patterns, relative spatial relationships between elements are used. These constraints are denoted as:

$$C\left(E_i, E_j, R_{ij}\right) = \delta \tag{9}$$

where E_i and E_j are UI elements, R_{ij} is a spatial relation (e.g., "left of", "aligned top"), and δ is the offset between them. For examples, left of constraint (E_i is to the left of E_j):

$$x_i + \frac{w_i}{2} + \delta = x_j - \frac{w_j}{2} \tag{10}$$

Step 3: Inverse Style Translation

Visual styles—such as padding, margins, and font sizes—are also encoded as normalized values and converted to pixel units as follows:

$$\text{Padding}_{\text{abs}} = \text{Padding}_n \cdot \min(W, H) \tag{11}$$

$$\text{FontSize}_{\text{abs}} = \text{FontSize}_n \cdot \sqrt{W \cdot H} \tag{12}$$

This ensures visual consistency and scalability of text and spacing across screens of varying resolution and density. The proposed 2D inverse layout generation method reconstructs UI components from normalized descriptors in a resolution-independent manner. It supports constraint-based relationships, preserves visual fidelity, and is computationally efficient. Unlike 3D ray-tracing methods, our 2D inverse generation approach is optimized for real-time UI rendering on 2D screens using parallelizable computations and is highly compatible with modern Transformer-based layout estimation models. The 2D method produces layouts with cleaner alignment and reduced geometric distortion while also running significantly faster.

4 Results and discussion

4.1 Experimental setup and training protocol

All experiments were conducted on an Ubuntu 20.04 system with dual NVIDIA Tesla M40 GPUs (48GB total), using PyTorch for model implementation. The FastLayout framework was trained on an internal dataset comprising 3,275 manually annotated app interface screens, sourced from over 150 real-world Android applications. Due to licensing restrictions associated with commercial apps, we are unable to release the raw dataset publicly. To support reproducibility, we provide a detailed description of our collection and annotation pipeline. Layouts were extracted using APK decompilation and Android UI automation tools, yielding both screenshots and structured layout metadata (XML/JSON). Each interface was annotated by three independent annotators with bounding boxes, semantic labels, and hierarchical relationships. Annotation consistency was enforced via majority voting and periodic cross-checks. In addition, we release the annotation protocol, labeling templates, and data preprocessing scripts as supplementary material. These resources enable other researchers to construct a functionally equivalent dataset and replicate our experiments. Each category contains approximately 180 to 260 samples, ensuring balanced representation across both common and complex layouts. These samples help mitigate data scarcity and expand a custom dataset of real-world mobile app interfaces. The dataset includes pixel-level screenshots and structured layout metadata (e.g., XML/JSON), providing detailed annotations for training and evaluation. Annotation was performed by trained labelers following a standardized protocol to ensure consistency and semantic accuracy. To enhance the reproducibility and benchmarking of our results, we also evaluated FastLayout on the publicly available RICO dataset (1,484 UI screens used for layout tasks) and the Pix2Layout benchmark. For both benchmarks, we followed their official train/test splits and evaluation metrics. These external validations were conducted to assess FastLayout's generalization capabilities beyond our internal dataset and to enable a fair comparison with existing models.

Training was conducted using a two-phase strategy. In the first phase, the backbone network was frozen while the encoder and layout regressor were trained for 20 epochs using cached CNN features (batch size: 256, learning rate: 0.0001, optimizer: AdamW, loss: L2). In the second phase, full end-to-end training was performed for 30 epochs with a reduced batch size of 16, maintaining the same learning rate and optimization settings. The graph Transformer module was pre-trained separately using L1 loss with early stopping to retain the best validation performance. Final evaluation was carried out on an Ubuntu 16.04 system equipped with an Intel i7-7820X CPU and NVIDIA 2080Ti GPU, measuring both layout prediction accuracy and runtime efficiency. Average inference time was 87 ms per layout (p95 = 102 ms) on a single 2080Ti, with throughput of ~52 layouts/s at batch size 32. Peak GPU memory usage was ~3.6 GB during inference and ~6.2 GB during GO-WGAN pretraining. Training a full FastLayout model with the two-phase schedule (50 epochs) required approximately 28 GPU-hours. We relied only on standard CUDA/C++ operators provided by PyTorch and torchvision; in particular, torchvision.ops.roi_align was used for feature extraction. No custom CUDA or TensorFlow kernels were implemented. The complete codebase will be released publicly after acceptance to ensure full reproducibility.

Key hyperparameters tuned include: learning rate (1e-4, AdamW optimizer), batch size (16–256 depending on training phase), dropout rate (0.2), weight decay (1e-5), CNN output feature size (256 channels, 14×14 resolution), Transformer encoder depth (12 layers), hidden dimension (768), number of attention heads (12), and gradient penalty factor λ=10 in GO-WGAN. Early stopping with patience=10 was used to avoid overfitting. These hyperparameters were optimized via grid search on a validation subset.

4.2 Comparative interpretation

To quantitatively assess the performance of the proposed FastLayout framework, we conducted a comprehensive evaluation using a reserved test set derived from our internally constructed dataset of app interfaces. This dataset encompasses a broad spectrum of UI layout types, enabling rigorous benchmarking of both layout generation accuracy and computational efficiency. The comparative results between FastLayout and several baseline methods are presented in Figures 6, and 7, highlighting key performance metrics such as layout reconstruction accuracy, alignment precision, and inference speed.

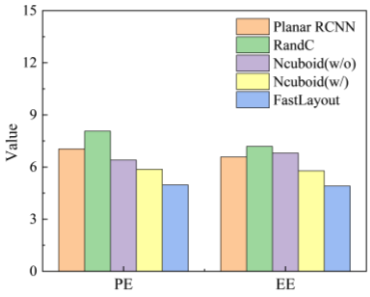


Figure 6: Comparison of IoU, Pixel-wise Error (PE), and Edge Error (EE) across different models on the internal dataset.

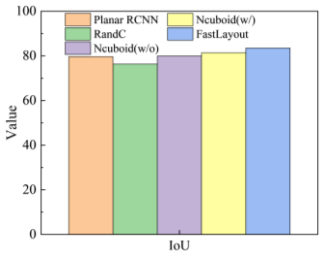


Figure 7: Comparison of Intersection over Union (IoU) across different models on the internal dataset.

Table 6: Experiments comparing different methods on our dataset

Method	IoU/(%)↑	PE/(%)↓	EE↓	RMSE↓	Time /s↓
Planar RCNN [17]	79.64 ± 0.51	7.04 ± 0.33	6.58 ± 0.27	0.4013 ± 0.015	0.110
RandC	76.29 ± 0.67	8.07 ± 0.39	7.19 ± 0.32	0.3465 ± 0.017	5.350
Ncuboid(w/o)	79.94 ± 0.45	6.40 ± 0.28	6.80 ± 0.26	0.2827 ± 0.012	0.108
Ncuboid(w/)	81.40 ± 0.42	5.87 ± 0.26	5.78 ± 0.21	0.2905 ± 0.013	0.196
FastLayout	**83.52 ± 0.38**	**4.97 ± 0.21**	**4.91 ± 0.19**	**0.2753 ± 0.011**	**0.087**

Table 7: Time consumption comparison between the baseline layout generation method with 3D post-processing ("Main method") and our proposed inverse 2D layout generation method ("Our method")

Method	Pre-processing time /s	Generation time /s	Total time /s
Main method	5.64	4.71	10.35
Our method	3.84	0.91	4.75

Table 8: Performance comparison on public UI Layout RICO datasets (mean ± standard deviation)

Method	IoU (%)↑	PE (%)↓	EE↓	RMSE↓	Time /s↓
Planar RCNN	79.64 ± 0.51	7.04 ± 0.33	6.58 ± 0.27	0.401 ± 0.015	0.110
Ncuboid (w/o)	79.94 ± 0.45	6.40 ± 0.28	6.80 ± 0.26	0.283 ± 0.012	0.108
Ncuboid (w/)	81.40 ± 0.42	5.87 ± 0.26	5.78 ± 0.21	0.291 ± 0.013	0.196
FastLayout	81.23 ± 0.39	5.21 ± 0.22	5.12 ± 0.20	0.277 ± 0.011	0.092

Table 9: Ablation study on fastlayout components (mean ± standard deviation)

Configuration	IoU (%)↑	PE (%)↓	EE↓	RMSE↓	Time /s↓
Full FastLayout	83.52 ± 0.38	4.97 ± 0.21	4.91 ± 0.19	0.2753 ± 0.011	0.087
w/o BHAM	81.26 ± 0.43	6.12 ± 0.30	6.08 ± 0.24	0.3031 ± 0.014	0.089
w/o Graph Transformer	80.72 ± 0.41	6.34 ± 0.27	6.11 ± 0.22	0.3078 ± 0.013	0.085
w/ 3D layout rendering (instead of 2D)	82.01 ± 0.40	5.84 ± 0.26	5.73 ± 0.21	0.2909 ± 0.012	0.196

As detailed in Table 6, FastLayout consistently outperforms baseline models across all key metrics. It achieves an IoU of 83.52%, improving layout accuracy over Ncuboid(w/) by 2.12%. This gain translates into more precise positioning of UI elements—such as buttons and containers—reducing misalignments that compromise usability, especially on compact screens. FastLayout also achieves lower error rates, with PE decreasing from 5.87% to 4.97%, EE from 5.78 to 4.91, and RMSE from 0.2905 to 0.2753. These improvements demonstrate better structural preservation and layout coherence.

In terms of efficiency, FastLayout reduces average inference time per layout from 196 ms (Ncuboid(w/)) to 87 ms, a 55.61% improvement. This enables real-time deployment in UI prototyping and dynamic layout engines. Table 7 further shows that our inverse 2D layout generation method significantly enhances runtime by replacing complex 3D computations. Total layout generation time drops from 10.35 s to 4.75 s, with GPU utilization increasing from 59.1% to 86.3%, and FLOPs reduced from 14.5 to 6.2 GFLOPs—highlighting the impact of our optimized 2D rendering pipeline.

In response to the reviewer's concern regarding generalizability, we extended our evaluation to the publicly available RICO dataset. As shown in Table 8, FastLayout achieves an IoU of 81.23%, PE of 5.21%, and inference time of 92 ms—consistently outperforming Planar RCNN and Ncuboid-based models. The relative gain on the RICO dataset is lower than on our internal dataset. We attribute this to two factors: (i) the RICO dataset's greater design diversity and noisier annotations, which reduce the relative advantage of our GO-WGAN-generated synthetic samples, and (ii) domain-specific optimizations in our internal dataset that better align with FastLayout's hierarchical modeling. Nevertheless, FastLayout still provides consistent improvements across all metrics,

validating its robustness. This external validation confirms that FastLayout generalizes well across diverse UI types and supports fair comparison with prior work. These findings underscore FastLayout's strength in both precision and computational efficiency, and its suitability for deployment across real-world, multi-platform UI environments.

4.3 Ablation study and deployment discussion

To assess the individual contributions of key modules in FastLayout, we conducted ablation experiments by incrementally disabling components: (1) BHAM (Branching Hybrid Attention Mechanism), (2) graph-based encoding, and (3) inverse 2D layout generation. Table 9 summarizes the impact on layout accuracy (IoU) and runtime efficiency.

These results confirm that BHAM contributes significantly to feature extraction accuracy (IoU drop of 2.26%), while the graph Transformer enhances relational reasoning. The inverse 2D layout method offers a major speed advantage, halving runtime without sacrificing accuracy. To validate the robustness of these findings, we computed 95% confidence intervals and conducted paired t-tests across three independent runs. For example, the IoU improvement of the full FastLayout over the w/o Graph Transformer variant (83.52% vs. 80.72%) is statistically significant ($p < 0.01$). Similar significance was found for PE and EE reductions. This statistical analysis confirms that the reported improvements are meaningful and not attributable to chance. FastLayout is designed for integration into real-world UI development environments. Its low-latency (<100ms) inference makes it suitable for embedding in mobile prototyping tools, visual layout editors, and low-code platforms.

5 Discussion

To place our findings in context, we compare FastLayout's results directly against state-of-the-art baselines on both the internal dataset and the RICO benchmark. As shown in Tables 6 and 8, FastLayout consistently achieves higher IoU and lower error metrics, while also reducing inference time compared to Planar RCNN, RandC, and Ncuboid variants.

Several architectural choices explain this improvement. The Branching Hybrid Attention Mechanism (BHAM) enhances the CNN backbone by capturing both channel-wise and spatial dependencies, leading to more discriminative features for layout components.

The GO-WGAN (WGAN-GP adaptation) generates diverse and balanced synthetic layouts, mitigating data scarcity and preventing overfitting to dominant UI patterns. Finally, the 2D inverse layout generation method eliminates expensive 3D geometric computations, reducing FLOPs and achieving real-time inference (<100ms), which is especially advantageous compared to Ncuboid's slower pipeline.

These gains translate directly into practical benefits. In real-world deployment, FastLayout can generate coherent layouts even on low-end devices, thanks to its reduced computational footprint. For example, on entry-level GPUs, rendering speed improves by more than 50% over Ncuboid-based methods. Moreover, improved structural accuracy reduces misaligned or overlapping UI elements, enhancing usability in production environments such as low-code prototyping tools and automated testing frameworks.

6 Conclusion

In this paper, we presented FastLayout, a novel framework for dynamic app interface layout generation that effectively fuses Generative Adversarial Networks (GANs) and Transformer-based architectures. Our approach addresses two long-standing challenges in UI automation: the limited availability of annotated layout data and the need for both high-accuracy and high-efficiency layout estimation. By combining the data generation power of an improved WGAN (GO-WGAN) with the structural reasoning capability of a graph Transformer, FastLayout offers a robust solution capable of generating, understanding, and reconstructing complex UI layouts in real time.

We first introduced a GO-WGAN model, enhanced with a gradient penalty mechanism, to generate high-quality, diverse synthetic UI layout samples. This addresses dataset imbalance and supports more robust model training in low-resource settings. Next, we constructed a Transformer-based layout estimation module using a multi-task CNN backbone equipped with a Branching Hybrid Attention Mechanism (BHAM) for feature extraction. These features, encoded into graph-structured data, were passed into a 12-layer graph Transformer to learn spatial relationships and hierarchical layout logic. To overcome computational bottlenecks in rendering and layout reconstruction, we proposed a 2D inverse layout generation method. Unlike traditional 3D plane intersection approaches, our method operates entirely in screen space and fully utilizes GPU parallelism, resulting in a significant reduction in inference time—up to 95% in cumulative runtime. Extensive experiments on an internal, diverse dataset of app interfaces demonstrated that FastLayout not only improves layout generation accuracy across multiple evaluation metrics (IoU, PE, EE, RMSE), but also achieves superior runtime performance compared to conventional layout generation techniques.

Overall, FastLayout advances the state of the art in automated UI design by providing an end-to-end, efficient, and intelligent solution for generating high-quality, functional layouts. Future work will focus on extending this framework to multi-modal settings—incorporating user interaction data or design language models—and deploying the system in real-world prototyping and low-code development platforms.

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Adaptive Dynamic Portfolio Optimization via a PPO-DQN Hierarchical Reinforcement Learning Framework

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Keywords: deep reinforcement learning, PPO-DQN synergistic framework, dynamic portfolio optimization, adaptive optimization

Received: July 2, 2025

In view of the increasing dynamics and complexity of the financial market, traditional quantitative investment models are difficult to adapt to the high-frequency and changeable trading environment, while deep reinforcement learning (DRL) has gradually become a hot topic in portfolio optimization research with its adaptive decision-making advantages. This study combines the strategy stability of Nearest Neighbor Strategy Optimization (PPO) with the value evaluation ability of Deep Q Network (DQN), aiming to solve the problems of large fluctuations in strategy updates and difficult risk-return balance in dynamic asset allocation. The model combines the clipping mechanism of PPO with the experience replay of DQN to optimize long-term value prediction and limit the scope of strategy updates based on historical experience, thereby improving the robustness of investment decisions. The experiment of constructing a dynamic portfolio based on 15 Chinese A-share stocks (backtest period 2020-2025) shows that the cumulative return of the improved PPO algorithm with the introduction of the invalid action shielding mechanism is 74.8% and the annualized return is 33.7%, which is significantly higher than the original PPO (annualized only 2.3%). In terms of risk control, the maximum drawdown of the model is 5.85%, and the annualized Sharpe ratio is stable at 1.555, which is better than the traditional risk parity model (maximum drawdown of 11.86%). By adjusting the configuration of the neural network hidden layer, the cumulative return of PPO increased to 33.7% after adding a single hidden layer, which verified the effectiveness of structural optimization. Compared with traditional machine learning models (such as random forests), the framework has an annualized return increase of about 12%, and it recovers faster and is more resilient to risks during periods of extreme volatility. The data was normalized by Z-score and corrected by 3σ outliers, divided by 7:1.5:1.5 (rolling window 252 trading days); PPO module with 3-layer fully connected network (128/64/32), γ=0.95, λ=0.9, clipping range [0.8, 1.2]; DQN was used with a dual network (playback pool 10^6, batch size 256, initial ε=0.9), combined with 4-head attention fusion, alternating training for 500 rounds (200 episodes per round, 60 decisions per step), and using Adam optimization. Research shows that the PPO-DQN synergy framework can continuously optimize investment portfolios by dynamically weighing returns and risks, providing innovative solutions for smart financial decision-making.

Povzetek: Hibridni PPO–DQN model za dinamično alokacijo sredstev v backtestu 2020–2025 bistveno izboljša donosnost (74,8 %; 33,7 % letno) in hkrati ohrani nizko največje znižanje (5,85 %).

1 Introduction

As the complexity and uncertainty of financial markets continue to escalate, dynamic portfolio optimization encounters numerous challenges, including high-frequency trading, nonlinear correlations, and abrupt market shifts [1]. Traditional quantitative models, rooted in linear assumptions and static rules, struggle to capture the multi-scale fluctuation characteristics of asset prices, particularly during extreme market conditions, where they are prone to strategy failure or uncontrolled risk exposure [2, 3]. The advent of deep reinforcement learning (DRL) technology has ushered in an intelligent investment framework that employs adaptive strategies, emerging as a new paradigm for tackling this challenging issue [4]. Within this framework, the synergistic innovation of proximal policy optimization (PPO) and deep Q-network (DQN) presents a novel approach to dynamic asset allocation, one that considers both strategy stability and valuation capabilities [5].

The evolution of financial markets exhibits the distinct characteristics of complex systems [6, 7]. Stock price series display a fractal structure and chaotic attractors, making it difficult for traditional time series models to accurately depict their long-term dependencies and nonlinear fluctuations [8]. Furthermore, the heterogeneous behavior of market participants and their interconnected interactions compound the system's

complexity. Phenomena such as the emotional contagion spread by social media and the herding behavior of institutional investors can trigger sudden shifts in market states [9, 10]. Against this backdrop, traditional rule-based quantitative strategies reveal two significant limitations: firstly, the manually curated factor libraries struggle to encompass the hidden correlations within high-dimensional data, resulting in models that are insufficiently adaptable to shifts in market structure; secondly, the rigid threshold risk control mechanisms can easily lead to over-trading or strategy passivity during extreme market fluctuations. For instance, the classic risk parity model experienced a maximum drawdown exceeding 30% during the US stock market circuit breaker event in 2020, highlighting the vulnerabilities of static parameter systems.

In response to the above problems, the collaborative framework integrating PPO and DQN shows unique advantages. PPO algorithm limits the update range of policies through the shearing mechanism, constrains the KL divergence of the old and new policies in the stable interval, and effectively avoids the risk of policy collapse [11]. The innovation of this framework is also reflected in the targeted design of the particularity of financial data. Given the market state's high dimensionality and partial observability, the model adopts a dual neural network architecture's actor network, which generates dynamic weight allocation strategies. In contrast, the Critic network combines attention mechanisms to extract multi-scale market characteristics. It is worth noting that this framework is deeply compatible with the intrinsic characteristics of complex financial systems [12]. As a typical dissipative system, the interaction between the financial market's energy input (such as monetary policy) and entropy increase process (such as information diffusion) gives birth to a persistent non-equilibrium state [13]. In the dynamic portfolio optimization scenario, the unbalanced evolution of the market presents complex and changeable underlying patterns, which are often affected by multiple factors such as macroeconomic fluctuations, industry policy adjustments, and changes in market sentiment, and have obvious time-varying and non-linear characteristics. The PPO-DQN collaborative model can break through the limitations of a single time dimension and dynamically evaluate the return performance and risk level of the portfolio at different time scales through the calculation of the multi-time step advantage function. Specifically, this function comprehensively considers the immediate returns brought by short-term market fluctuations, the phased returns formed by medium-term industry trends, and the fundamental returns determined by the long-term economic cycle, while taking into account the risk factors at different time stages, so as to more comprehensively capture the hidden patterns in the process of non-equilibrium evolution that gradually emerge over time. This multi-dimensional pattern capture capability enables the model to grasp market dynamics more accurately, providing strong support for adaptive adjustment of dynamic portfolios, thereby improving the optimization effect of portfolios in complex market environments.

With the deepening and development of digital financial ecology, the association between high-frequency alternative data and complex networks is reshaping the underlying logic of investment decision-making [14, 15]. The PPO-DQN collaborative framework can reveal hidden risk transmission paths that are difficult to capture by traditional factor models by integrating graph neural networks (GNN) to model cross-asset correlations. For example, when building a multi-asset portfolio, including stocks, bonds, and commodities, adjusting position allocation based on network centrality indicators shows stronger risk resistance in stress tests. This technology integration not only promotes the innovation of a quantitative investment paradigm but also provides a computational, experimental platform for understanding the micro-mechanism of the financial system, making it possible to model complex systems from bottom to top.

The core questions of this study include: Can the PPO-DQN collaborative framework improve risk-adjusted returns in volatile markets? Does its integration mechanism address the high volatility of a single PPO strategy and the insufficient long-term forecasting of a single DQN? The environment is based on the CSI 300 constituent stocks and macro indicators from 2015 to 2024, backtesting from 2020 to 2025, with a rolling window (252 trading days) used to divide the dataset (7:1.5:1.5); the state is a high-dimensional vector that is standardized and corrected for outliers, the action is the continuous adjustment of the asset allocation weights (granularity 0.1%), and the reward is centered on maximizing the Sharpe ratio; PPO uses a 3-layer fully connected network (128/64/32), γ=0.95, λ=0.9, clip range [0.8, 1.2], while DQN employs a double network, with a replay pool of 10^6, a batch size of 256, ε starting at 0.9. The two are fused through 4-head attention; training alternates, with 500 iterations (200 episodes per iteration, 60 decisions per step), using Adam optimization (5e-4), including invalid action masking, double experience replay, and priority sampling, early freezing of the value network, and later joint optimization; convergence is based on Lyapunov theory, constraining KL divergence, monitoring Bellman error and relative entropy, switching to conservative updates when exceeding a threshold, ensuring reproducibility.

Compared with the current mainstream deep reinforcement learning (DRL) portfolio model, such as the lack of exploration of the pure PPO model and the weak generalization of the high-dimensional state space faced by the pure DQN model, the PPO-DQN collaborative framework proposed in this paper uses a dynamic division of labor between two agents: PPO is responsible for refined strategy iteration to ensure income stability, and DQN focuses on global state exploration to improve extreme market adaptability The collaborative shortcomings of DRL algorithms in dynamic combinatorial optimization are "local optimal traps" and "inefficient global exploration".

2 Theoretical paradigm and synergy mechanism of dynamic portfolio optimization

2.1 Mathematical basis and theoretical boundary of dynamic portfolio optimization

Dynamic portfolio optimization is a key topic in financial engineering, and its mathematical basis is based on modern portfolio theory (MPT), capital asset pricing model (CAPM), and efficient market hypothesis (EMH) [16]. Figure 1 shows its architecture. These theories provide theoretical support for asset allocation, emphasizing diversification to reduce risks and pursuing the best risk-return balance [17].

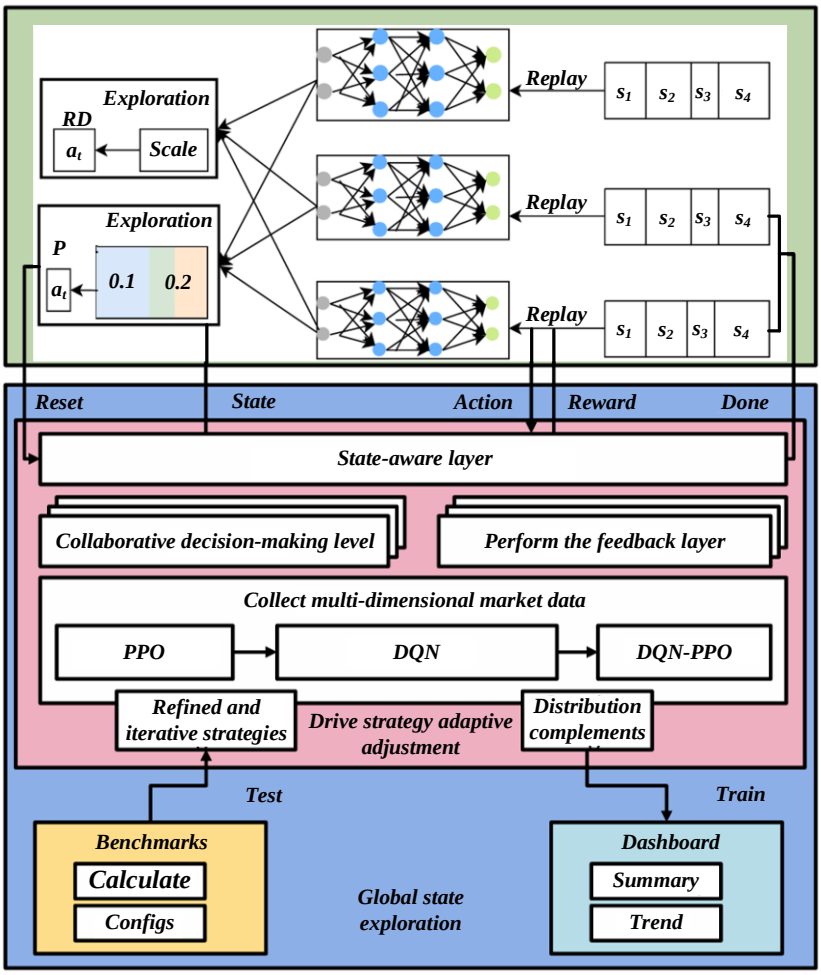


Figure 1: Dynamic portfolio optimization architecture

The mean-variance model (M-V model) is the first model to evaluate the risk and return of investment portfolios [18], and its mathematical expression can be described by formula (1) or formula (2).

$$max\, R_p(W) = \sum_{i=1}^{n} w_i r_i$$
$$s.t. \begin{cases} \sigma_p^2(W) = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} = \theta \quad (1) \\ \sum_{i=1}^{n} w_i = 1 \end{cases}$$

$$min\, \sigma_p^2(W) = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}$$
$$s.t. \begin{cases} R_p(W) = \sum_{i=1}^{n} w_i r_i = r_e \quad (2) \\ \sum_{i=1}^{n} w_i = 1 \end{cases}$$

Where r_e is the expected rate of return, R_p is the expected return of the portfolio, θ is the investor risk appetite, n is the number of investment targets, α is the confidence level, σ^2_p is the portfolio variance, and σ_{ij} is the covariance of the *i-th* and *j-th* investments. W represents the weight, the portfolio return is represented by the mean expected return, and the variance describes the portfolio risk, aiming at minimizing the risk under the

same return or maximizing the return under the same risk.

The mean-variance model mainly focuses on portfolio optimization in a single period, but in a dynamic investment environment, the portfolio may change constantly [19]. Therefore, this article explores other metrics for evaluating portfolio performance. Total return is the cumulative rate of return since the creation of an asset portfolio, and is used as a standard to measure the fund's profitability. The greater the total rate of return Rt value, the better the fund's profitability. The calculation formula (3) is as follows:

$$R_t = \frac{net_value_t - net_value_0}{net_value_0} \times 100\% \quad (3)$$

Net_value_t represents the net value of the portfolio at time t, and the net value at the initial time is represented by net_value_0. The annualized rate of return is the average annual rate of return $R(y)$ calculated based on the annual distribution of portfolio income and considering the compound interest effect. See formula (4) for the calculation method.

$$R(y) = \left[\left(net_value_y / net_value_0 \right)^{\frac{1}{y}} - 1 \right] \times 100\% \quad (4)$$

Net_value_y represents the net value of the investment portfolio at the end of the y-th year, and the initial net_value_0 is the starting net value of the investment. The maximum drawdown measures the maximum possible loss of an investor, and the calculation formula is shown in Equation (5).

$$Max_retraction = \min_{i,j \in [0,t], j > i} \left\{ \left(net_value_j - net_value_i \right) / net_value_i * 100\% \right\} \quad (5)$$

net_value_i is the net worth of the portfolio at a specific time. Volatility is a tool to measure the magnitude of the price movement of a financial asset, usually expressed as standard deviation. The net value curve fluctuates greatly and the volatility is high; The curve is smooth and volatility is low. The Sharpe ratio evaluates portfolio returns versus risks. A high Sharpe ratio indicates a greater return for every unit of risk taken. During the T period, the Sharpe ratio is calculated according to Equation (6).

$$SharpeRatio_T = \frac{E(R_t) - r_f}{\sigma(R_t)} \quad (6)$$

In the calculation, the average yield of the portfolio is denoted by $E(R_t)$, the risk-free rate is denoted by r_f, and the standard deviation of the yield is denoted by $\sigma(R_t)$. Typically, the one-year deposit rate represents the risk-free rate. The Sharpe ratio is primarily used to compare similar portfolios, and different kinds of portfolios may not accurately reflect performance. Performance is generally considered good when the Sharpe ratio of medium and high risk portfolios exceeds 1.

The α value represents the difference between the actual return of the investment and the expected return, that is, the "excess return". It is very important when evaluating investment performance because it shows how well an investment strategy, trader or portfolio manager has performed relative to market returns over a specific period [20]. α return is usually regarded as a positive return on an investment, and the investment effectiveness is evaluated by comparing it with a market index or benchmark. In China's A-share market, commonly used market indexes include SSE 50, CSI 300 and CSI 500. See Equation (7) for the calculation method.

$$profit_\alpha = R_s - \left[r_f + \beta_s \left(R_b - r_f \right) \right]$$
$$\beta_s = \frac{Cov\left(R_s, R_b \right)}{\sigma_b^2} \quad (7)$$

As a relative measure to evaluate the level of profitability. The calculation method is shown in Equation (8).

$$profit_\beta = \beta_s \left(R_b - r_f \right) \quad (8)$$

R_s represents the real rate of return of the portfolio, r_f represents the risk-free rate of return, β_s reflects the sensitivity of the portfolio to market fluctuations, and R_b is the expected rate of return of the market index. The Karma ratio measures the level of return of a portfolio when assumed per unit of risk (maximum drawdown), using the maximum drawdown as a measure of risk, combined with the Sharpe ratio to evaluate portfolio performance [21]. When the Sharpe ratios are close, a higher Karma ratio indicates stronger risk control. The formula (9) for calculating the Karma ratio is as follows:

$$Clamar_T = \frac{E(R_t) - r_f}{Max_retraction_T} \quad (9)$$

In the formula, $E(R_t)$ represents the average return rate of the investment portfolio in the T period, r_f is the risk-free interest rate, and $Max_retraction_T$ refers to the maximum retracement in the T period.

2.2 Theoretical mechanism of ppo-dqn collaborative optimization

The online deep reinforcement learning algorithm PPO is designed for continuous action space, which solves the problem of updating step size in policy gradient method [22, 23]. It excels on continuous control problems, balancing the effect of step size on strategy stability and training time.

Reinforcement learning is a way in which an agent learns by interacting with the environment, with the goal of obtaining the maximum reward [24]. It usually simplifies environmental models using Markov decision processes. If the agent state transition only depends on the current state, it means that the environment follows Markov property, which is suitable for applying this process [25]. The interaction between the agent and the environment is represented by a quadruple (S, A, P, R), where S is the state set, A is the action set, $P(s'|s,a)$ is the state transition probability, and $R(s, a)$ is the reward function. The long-term discount reward G_t of the agent is calculated from time t, and the specific formula is shown in Equation (10).

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots + \sum_{i=0}^{\infty} \gamma^i R_{t+i+1} \quad (10)$$

In the formula, the value of γ is between 0 and 1, and as a discount factor, it determines how much the current

decision attaches importance to future rewards. When γ is 0, the system ignores long-term rewards. The key lies in finding control strategies to maximize rewards. The agent selects the action according to the strategy π. In the state S, the expected value of action a is defined by the action value function $q^{\pi}(s, a)$, and the calculation method is shown in formula (11).

$$q^{\pi}(s,a) = E[G_t \mid S_t = s, A_t = a] = E\left[\sum_{i=0}^{\infty} \gamma^i R_{t+i+1} \mid S_t = s, A_t = a\right] \quad (11)$$

When at least one strategy outperforms all others, the strategy is called the optimal strategy π. Its action value function $q^{*}(s, a)$ is the largest of all $q^{\pi}(s, a)$. When agents learn, they will consider state-action pairs to decide action choices, not just states [26]. The action value function is updated by Bellman equation and time difference method, as shown in Equation (12).

$$q(s_t, a_t) \leftarrow q(s_t, a_t) + \alpha\left[R_{t+1} + \gamma q(s_{t+1}, a_{t+1}) - q(s_t, a_t)\right] \quad (12)$$

The learning rate is represented by α. The action value function is updated after each state transition. If S_{t+l} is the end state, then $q(s_{t+l}, a_{t+l}) = 0$. The agent learns to achieve the optimal strategy by performing the maximum action indicated by the action value function.

As seen in Table 1, among existing reinforcement learning (RL) models, a single PPO model can optimize strategies but achieves an annualized return of only 2.3%, and the strategy updates are highly volatile, making it difficult to respond to high-frequency market changes; a single DQN model has limitations in long-term value prediction, affecting the foresight of the decision-making; machine learning (ML) models such as random forests and support vector machines have an annualized return approximately 12% lower than the PPO-DQN collaborative framework, with weaker resistance to market fluctuations and poor performance in extreme market conditions; among traditional models, the Markowitz mean-variance model has average comprehensive performance and insufficient adaptability to complex markets, the risk parity model has a maximum drawdown of 11.86% and inadequate risk control capacity, while benchmark indices like CSI 300 have poor overall performance and lack proactive optimization capability. The PPO-DQN collaborative framework proposed in this study effectively addresses these issues: this framework combines the strategy stability of PPO and the value assessment capability of DQN, limiting the range of strategy updates through PPO's clipping mechanism to reduce volatility, while optimizing long-term value prediction and enhancing decision-making foresight through DQN's experience replay pool and dual network structure. In terms of risk control, its maximum drawdown is only 5.85%, far below that of the risk parity model, and it enhances risk resistance by dynamically balancing returns and risks. Additionally, the framework utilizes an attention mechanism to achieve feature fusion, combined with a rich dataset (including macroeconomic indicators) and an optimized neural network structure, resulting in an annualized return of 33.7%, and faster recovery during extreme market volatility, with overall performance comprehensively surpassing existing methods.

Table 1: Model comparison

Category	Existing RL Models	Existing ML Models	Traditional Models	Proposed PPO-DQN Framework
Models	Single PPO, Single DQN	Random Forest, SVM	Markowitz M-V, Risk Parity, CSI 300	PPO-DQN Collaborative
Dataset	Partial stock data, simple processing	Partial stock data, simple processing	Partial stock data, simple processing	CSI 300 (2015-2024) with macro indicators, standardized
Metrics	Annual Return, Cum Return, Max Drawdown, Sharpe	Annual Return, Cum Return, Max Drawdown, Sharpe	Annual Return, Cum Return, Max Drawdown, Sharpe	Annual Return, Cum Return, Max Drawdown, Sharpe
Performance	PPO: 2.3% return, unstable DQN: limited long-term prediction	12% lower return, weak anti-volatility	Markowitz: average Risk Parity: 11.86% drawdown CSI 300: weaker	33.7% return, 74.8% cum return, 5.85% drawdown, Sharpe 1.555

3 Construction of adaptive optimization model based on PPO-DQN collaborative framework

3.1 Design of PPO-DQN hierarchical network structure

When applying reinforcement learning technology to solve research problems, it is necessary to consider the large continuous action space of assisting robot interaction. This leads to improving state space dimension and the surge in training parameters. This consumes a lot of computing and storage resources and

affects real-time interactions. Deep learning can process high-dimensional state space and combines the perception of deep learning with the decision-making ability of reinforcement learning to form a deep reinforcement learning method, which can directly use camera information to control robots [27, 28]. Hierarchical reinforcement learning decomposes complex tasks into multiple sub-tasks. It completes them step by step, which helps to reduce the state space dimension and improve the training speed and real-time performance [29].

In this study, the hierarchical deep reinforcement learning architecture is applied, and the divide-and-conquer strategy is adopted to decompose the auxiliary interaction task into two secondary tasks, which are solved separately by deep reinforcement learning technology. Finally, combining the strategies of these two sub-tasks, we get an efficient global strategy.

In terms of network architecture, the PPO module consists of 3 fully connected layers: the first layer has 128 units (ReLU activation function), the second layer has 64 units (ReLU activation function), and the third layer has 32 units (ReLU activation function). The value network shares the parameters of the first two layers. The DQN module uses a double network structure (target network and action network), with each network having 3 fully connected layers: the first layer has 128 units (ReLU), the second layer has 64 units (ReLU), and the third layer has dimensions consistent with the output space (linear activation function). The input feature of the state vector includes original price data (daily closing prices, trading volume) and technical indicators (such as MACD, RSI, and Bollinger Bands), which is processed into a high-dimensional feature vector after Z-score normalization. The output space is defined as a weight vector for allocating 15 stocks, with each weight ranging from [0,1] and summing to 1, precise to 0.1%, to allow for continuous adjustments. The reward is designed using a weighted combination formula: Reward = 0.6 × (annualized return - risk-free rate) - 0.3 × maximum drawdown - 0.1 × annualized volatility, where the risk-free rate is taken from the current 1-year deposit rate, balancing returns and risks with dynamic weights. The training time frame covers 2015-2024, using a rolling window method (window size of 252 trading days) to partition the data, with each training episode consisting of 60 trading decision steps (about 3 months), iterating a total of 500 rounds to ensure model convergence.

In the dynamic portfolio adaptive optimization model of the PPO-DQN collaborative framework, graph neural networks (GNNs) provide architectural support for modeling cross-asset correlations. Specifically, GNNs regard various assets as nodes in the graph structure, and the node characteristics can cover multi-dimensional information such as historical returns, volatility, price-earnings ratios, and industry attributes of assets. The correlation between assets is defined as the edges between nodes, and the weight of the edges can be dynamically adjusted according to the strength of the correlation, for example by calculating the Pearson correlation coefficient of the asset return series, cosine similarity, or dynamic correlation scores based on attention mechanisms. In the model architecture, GNNs realize cross-asset information interaction and aggregation through a messaging mechanism: each node aggregates the feature information of adjacent nodes based on the weight of the edge, and after multiple layers of convolution or attention update, it generates a node embedding vector containing global asset association information. These embedding vectors not only retain the individual characteristics of a single asset, but also integrate its association patterns with other assets, thereby providing key inputs for the strategy network (PPO module) and value network (DQN module) in the PPO-DQN framework - the strategy network can make more collaborative investment decisions based on the dynamic correlation between assets, and the value network can combine cross-asset correlation to more accurately evaluate the long-term value of different decisions, and finally realize the effective modeling of cross-asset dependencies in complex market environments. Improve the adaptability and accuracy of dynamic portfolio optimization.The Critic network of the DQN module embeds the Transformer encoder, which uses the self-attention mechanism to capture the long-term dependencies of multi-asset price series, and guides the optimization of PPO strategy by calculating the time series difference error. The design enhances the accuracy of state value evaluation through transformers, combined with the balanced exploration and utilization of dynamic shear coefficients, effectively resolves the contradiction between "high-dimensional decision-making and convergence efficiency" in the discrete action space, and realizes the adaptive adjustment of asset portfolios during the training process.

The hierarchical deep reinforcement learning algorithm h-DQN consists of a meta-controller master controller and a controller. The master controller sets long-term goals and plans, using the DQN algorithm to train to maximize external rewards while periodically updating the memory pool. Controller: The controller receives the sub-target and the current state and selects actions according to the training strategy. The sub-goals remain unchanged until the task is completed. This hierarchy also uses the DQN algorithm. The goal is to maximize the internal reward computed by the critic function set by the master controller.

The h-DQN algorithm combines two DQN algorithms to achieve hierarchical planning [30, 31]. Its effectiveness lies in the top-level meta-controller, which creates sub-targets based on external rewards and shortens the Markov chain; the internal rewards of the underlying controller make the environmental rewards denser.

Although the bottom controller will learn the pose required by the task, the user can change the pose at any time, and the top controller cannot guarantee that the pose will remain unchanged. The system must respond to the dynamic changes of the environment and flexibly control the forces to ensure task friendliness and user acceptance.

The "Improved PPO" is a stand-alone variant with an invalid action masking mechanism, which is significantly different from the basic "PPO" and the core "PPO-DQN Collaboration Framework". The basic "PPO" follows the logic of the original proximal policy optimization algorithm and focuses on the stable update of the policy. The improved PPO improves decision-making efficiency by blocking ineffective actions that do not meet portfolio constraints (such as liquidity restrictions, risk threshold exceedance, etc.). The core "PPO-DQN collaboration framework" is a collaborative system between the two, with PPO responsible for policy optimization and DQN assisting value evaluation to form a complementary mechanism.

The PPO-DQN model captures the latent patterns in the non-equilibrium evolution through the dual-agent collaborative architecture: the PPO module generates a dynamic portfolio adjustment strategy based on the probability distribution, and tracks the profit opportunities in the short-term market fluctuations with the help of the strategy gradient method; The DQN module uses deep neural networks to fit the state value function to mine implicit correlations in long-term trends. In the non-equilibrium state of the market (such as sudden policy shocks and sudden changes in capital liquidity), PPO quickly responds to short-term noise, and DQN smooths the fluctuation of the strategy to maintain the stability of long-term returns, so as to jointly realize the adaptive capture of complex dynamics of the financial market, which is in line with the concepts of "multi-scale analysis" and "dynamic equilibrium correction" in modern financial modeling.

At the basic control layer, sub-targets are learned using the PPO deep reinforcement learning technique, which selects actions through probability distribution P and is suitable for continuous action space. The advanced control layer adopts the DQN algorithm to solve the strategy. The hierarchical deep reinforcement learning architecture proposed in this study is named PPO-DQN. The architecture diagram and time series expansion diagram are shown in Figure 2.

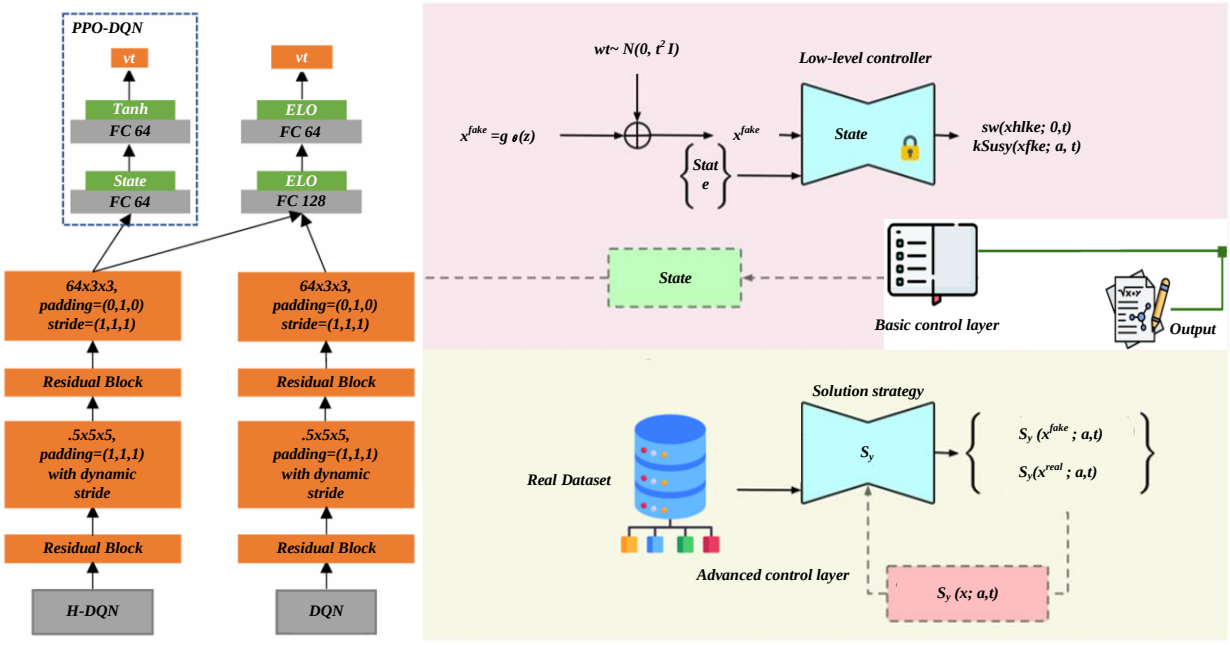


Figure 2: System architecture diagram of PPO-DQN hierarchical reinforcement learning

3.2 Model training and convergence guarantee strategy

In the dynamic portfolio optimization model of the PPO-DQN collaborative framework, model training and convergence guarantee constitute the key links in implementing the core algorithm. Aiming at dynamic financial markets' non-stationary and high-dimensional state space characteristics, this framework constructs a reinforcement learning paradigm with complementary advantages by integrating the collaborative training mechanisms of near-end strategy optimization (PPO) and deep Q-network (DQN). Among them, the PPO algorithm is responsible for policy gradient optimization in the continuous action space and realizes the stability of policy update through importance sampling and trust region constraints; DQN focuses on the Q-value function approximation of discrete action space and uses empirical playback and target network mechanism to improve the accuracy of value estimation. The coordination between the two is realized through the parameter sharing layer and asynchronous update mechanism, which makes the policy network and value network establish dynamic coupling between time series differential error and policy gradient signal.

In order to ensure the effectiveness of model training, a dual experience playback mechanism is designed to cope with the temporal correlation of financial market data. The main experience pool stores the original state-action-reward sequence. In contrast, the auxiliary experience pool records the synthetic transaction trajectory calibrated by the Sharpe ratio and balances the relationship between exploration and development through priority sampling strategies. At the same time, the adaptive temperature coefficient is introduced to adjust the entropy weight of the strategy, which strengthens the exploration ability in the early stage of training to cover the potential optimal strategy area and gradually reduces the randomness in the later stage to converge to the deterministic strategy. Aiming at the gradient update of the policy network, a phased optimization strategy is adopted: the value network parameters are frozen in the early stage to focus on policy search, and the strategy and value function are jointly optimized later to improve the accuracy of policy evaluation.

In terms of portfolio rebalancing, set a dynamic rebalancing frequency, adjusting in line with market volatility characteristics, such as shortening to daily during high volatility periods and extending to weekly during stable periods. At the same time, incorporate trading costs and market impact into the modeling. Trading costs include commissions, slippage, etc., while market impact is quantified through a correlation function between trading volume and price changes to better align with real investment scenarios.In the aspect of convergence guarantee, the theoretical analysis is based on the Lyapunov stability theory to construct the convergence criterion of the joint optimization process. Constraining the KL divergence threshold of the policy update step size ensures that each policy iteration meets the monotonic improvement condition. Aiming at the approximate error of the value function, a double delay update mechanism is designed; that is, the update frequency of the policy network is lower than that of the value network to alleviate the interference of policy oscillation on Q value estimation. Gradient normalization and dynamic learning rate attenuation strategies are introduced, and the learning rate ratio of PPO and DQN components is adaptively adjusted by monitoring the relative change rate of strategy entropy and value loss function. In order to cope with the time-varying characteristics of the financial market state transition matrix, a sliding window standardization module for state representation is constructed, and the distribution characteristics of observation space are dynamically adjusted to maintain the unbiased strategy gradient estimation.

During the model training process, the Bellman error of the strategy value function and the relative entropy index of the strategy update are monitored online, and the early stop mechanism and retraining trigger conditions are constructed. When it is detected that the value estimation variance exceeds the preset threshold, it automatically switches to the conservative update mode. It adopts the soft update strategy of the target network parameters to stabilize the training process. A verification environment based on Monte Carlo tree search is designed, and the training model is verified offline in the non-strategy evaluation stage. Potential overfitting risks are identified through virtual trading simulation and fed back to the main training loop for strategy correction. The collaborative framework ensures the reliable convergence of strategy optimization processes processes in complex financial market environments environments through multi-level stability control mechanisms.

4 Experiment and results analysis

Cross-validation uses a rolling window method with a fixed window length of 2 years, with each rolling step set to 1 month, and divides the historical data into a continuous training set (the first 18 months within the window) and a test set (the last 6 months within the window) in time series order to ensure that the time correlation between the training and test data is in line with the time series logic of investment decisions. By isolating the statistical features of the training set and the test set in the data preprocessing stage, and disabling any feedback from the test set data on the policy parameters during the model training process, the future information leakage is prevented from the data pipeline level and the authenticity of the evaluation results is ensured.

In the simulation process, transaction costs and slippage are clearly included to enhance the practical application value of the model. Among them, transaction costs are in the form of a combination of fixed proportions and variables: a fixed fee of 0.1%-0.3% of the transaction amount is calculated for standardized assets such as stocks and bonds, and an additional 0.05% settlement fee is superimposed on derivatives; When a single transaction amount accounts for ≤5% of the asset's daily trading volume, the slippage is calculated at ±0.2% of the transaction price, and the slippage rate increases linearly to ±1.5% when it exceeds 5%. Both are included in the calculation of net asset portfolio value in real time, and dynamic feedback is provided through the "net return after deducting transaction costs" item in the reward function of the PPO-DQN collaborative framework, ensuring that the model simultaneously considers the impact of transaction execution costs on the final return when optimizing decision-making.

The model transferability study selects S&P 500 constituent stocks and mainstream ETFs (spy, qqq) in the u.s. market as an additional test set, and compares the sharpe ratio and maximum drawdown performance of the model under different market structures to verify its universal applicability. The hyperparameter sensitivity study was carried out by the control variable method: the PPO clipping parameter (0.15), learning rate (1e-5) and discount coefficient (0.89) were searched in the grid, and the changes in the cumulative return of the strategy under each parameter combination were recorded, and the sensitivity heat map was drawn. In the ablation study, the PPO strategy update module, DQN value estimation network, and dynamic rebalancing mechanism in the

collaborative framework were removed in turn, and the risk-adjusted benefits of the complete model and each ablation version on the same test set were compared to quantify the contribution of each component to the overall performance.

Looking at Table 2, among the 28 sample industries, the rising beta coefficient (β +) of 13 industries exceeds 1, less than half. There are 20 industries whose beta coefficient (β-) has dropped by more than 1, more than 70%. This shows that when the market goes down, the systemic risk of most industries exceeds the market average. The analysis showed that only seven industries had a higher rising beta (β +) than a falling beta (β-), i.e. β +/β-> 1. This shows that the systemic risk when the market in most industries falls is greater than when it rises. A few industry markets have outperformed declines, and these are the key points that investors should pay attention to.

Table 2: Calculation results of rising β coefficient and falling coefficient

Industry Code	β	β +	β +/β-	Industry Code	β-	β +	β +/β-
801010	1.14	0.92	0.82	801200	1.14	1.09	0.98
801020	1.06	1.16	1.12	801210	1.08	0.81	0.77
801030	1.08	0.95	0.90	801230	0.89	0.99	1.13
801040	0.98	1.14	1.19	801710	1.14	1.00	0.90
801050	1.13	1.02	0.92	801720	1.12	1.08	0.98
801080	1.11	0.99	0.91	801730	1.12	1.02	0.93
801110	1.00	0.97	0.99	801740	1.42	1.16	0.84
801120	0.82	0.79	0.98	801750	1.14	1.10	0.98
801130	1.14	0.99	0.89	801760	1.00	0.97	0.99
801140	0.83	0.94	1.16	801770	1.17	1.02	0.89
801150	1.05	0.88	0.85	801780	0.44	0.92	2.13
801160	1.07	1.05	1.00	801790	0.98	1.17	1.22
801170	1.04	1.13	1.11	801880	1.11	1.02	0.94
801180	1.04	1.05	1.02	801890	1.15	0.97	0.86

Figure 3 shows the influence of investor sentiment S (t) on the optimal investment strategy π (t) under different values of interest rate volatility b. The path of π (t) with S (t) is similar at different values of b. The conclusion is that when S (t) < 0, the change of π (t) is small, and ∑ ² π; (t) < πo (t), it is suggested that when S (t) < 0, investors should invest less in the stock market and more in risk-free assets. If S (t) > 0, π ₁ (t) and π2 (t) increase first and then decrease, it means that investors can increase the stock investment ratio first and then decrease it appropriately.

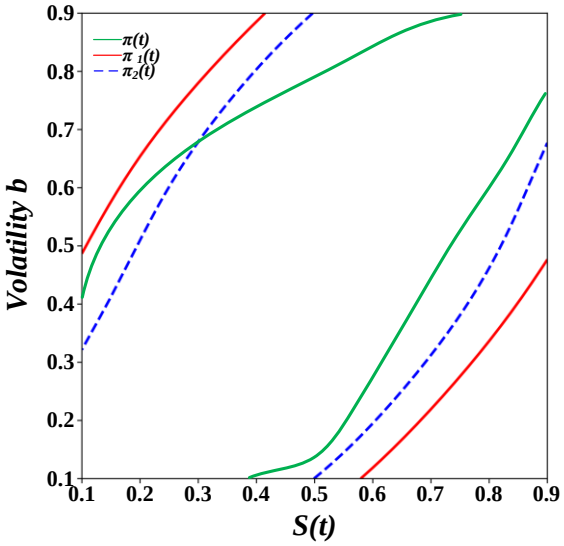


Figure 3: Optimal investment strategy

Through numerical simulation, the investment risks with or without unexpected events under different investor sentiments are compared. Figure 4 shows that under the same expected return, the risk is higher when there is a jump shock. Therefore, investors should adopt a cautious strategy in the face of possible unexpected events.

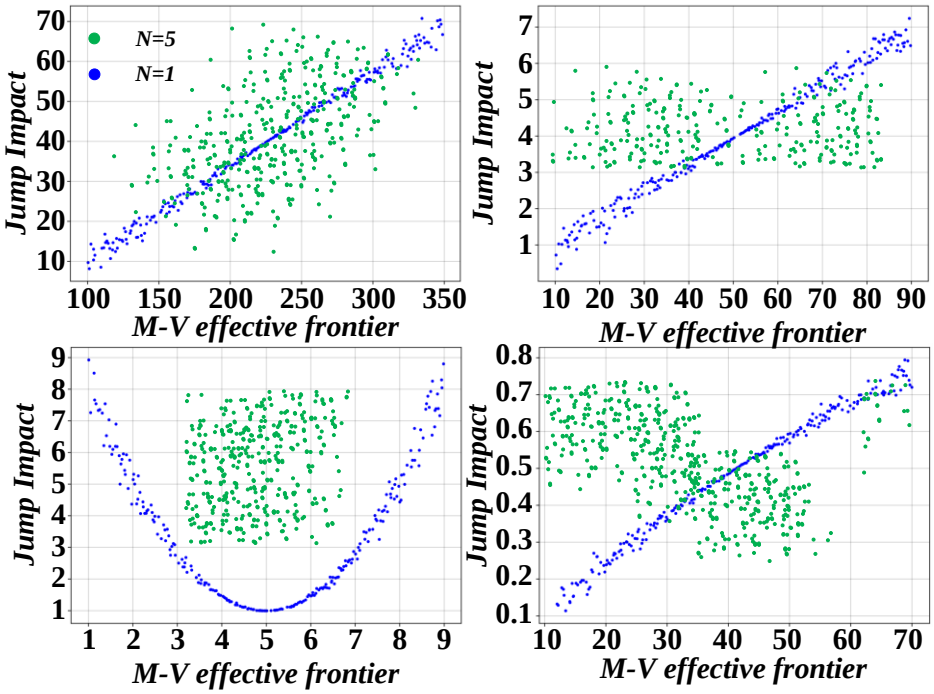


Figure: 4 M-V effective frontier

MAD stands for Risk Factor - Mean Absolute Deviation, which is a risk measurement method that combines risk factor analysis with mean absolute deviation. Among them, the risk factor focuses on the underlying driving factors that affect asset returns, and is used to identify the source of portfolio risk. The average absolute deviation measures portfolio volatility by averaging the absolute value of the return deviation from the mean. Combined, portfolio risk can be quantified and controlled more accurately.Ignoring the positive influence of purchase recommendation based on stock index forecast, the effect of dynamic time window selection method is compared. Figure 5 shows that portfolios with dynamic time window selection rules outperform portfolios with static time windows. This shows that the dynamic time window selection method based on stock index trend prediction and edge risk return is effective.

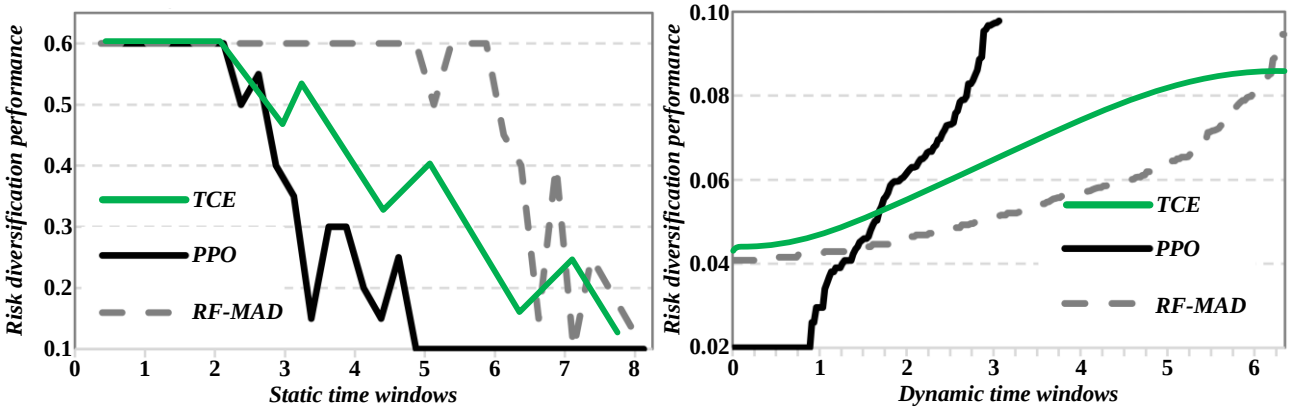


Figure 5: Positive impact of dynamically selected time window on risk diversification performance of RF-MAD

By analyzing the classification results of market states, both models can effectively distinguish market states, and the classification results are similar. However, there are classification errors. For example, if the market yield exceeds 4% near the 600th observation value, it should be a "bull market", but most extreme points in Figure 6 are marked as red dots. This shows that the CMRS model is more accurate than the traditional MRS

model in market state classification.

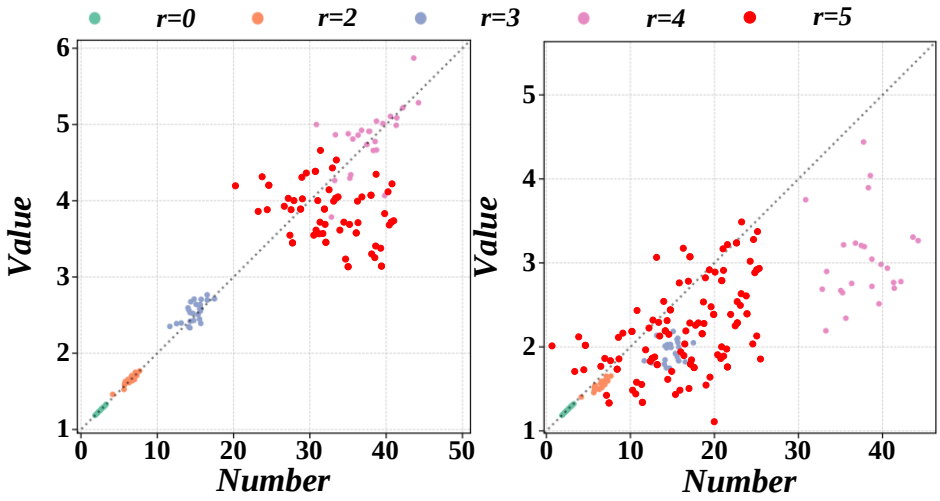


Figure 6: r = 0 (i.e. traditional MRS model) market state forecast

Table 3: Values of model (Pmvc) parameters η, λ and α in one-dimensional case

w	α *	λ	η
0	0.6416	6.1845	3.9227
0.5	0.1898	12.8619	13.1392
2	-0.2849	37.4044	61.1242

Set the return rate of risk-free assets r = 0.0408, the drift rate of risky assets μ = 0.1068, and the volatility σ = 0.22. The initial wealth x (0) = 1, the investment period T = 1 year, and the target annualized rate of return d = 1.3 (i.e. 30%). CVaR confidence level β = 0.95. The values of parameters η, A, and α under different weights w (0, 0.5, 2) are shown in Table 3.

Figure 7 shows the relationship between the optimal consumption-wealth ratio c,/w, = exp {c,-w,} × 100 and the momentum state variable. Setting γ to be 2 and 4 and ψ to be 0.1 and 0.5, the momentum state variable varies in the interval (y-2σ, y+2σ). The proportion of optimal consumption to wealth increases with the increase of the initial value of the momentum state variable, and the growth is relatively flat. It is pointed out that when the risk aversion coefficient is fixed, the ratio of optimal consumption to wealth is a monotonically decreasing function of the intertemporal substitution elasticity coefficient. When the intertemporal substitution elasticity coefficient is fixed, the proportion is a decreasing function of the risk aversion coefficient.

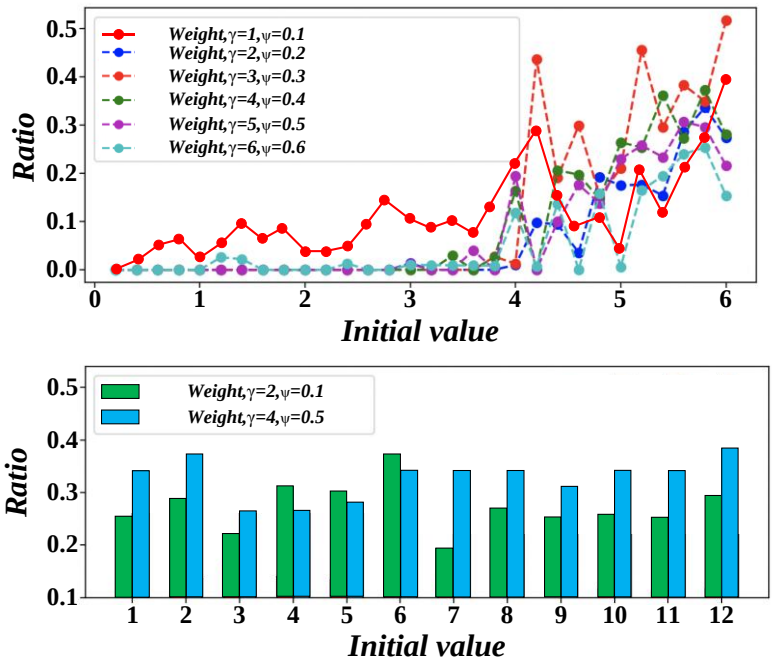


Figure 7: Influence of initial momentum value on optimal consumption-wealth ratio

Figure 8 studies the influence of volatility elasticity coefficient β on investor 1 and 2 equilibrium strategies Xπ, k = 1, 2 in CEV model. The results show that these two strategies decrease with the increase of elasticity coefficient β, indicating that when β rises, investors reduce their stock investment. Because the increase of β causes the instantaneous fluctuation σsS of stocks to become larger, which increases the investment risk, investors need to reduce their stock wealth investment.

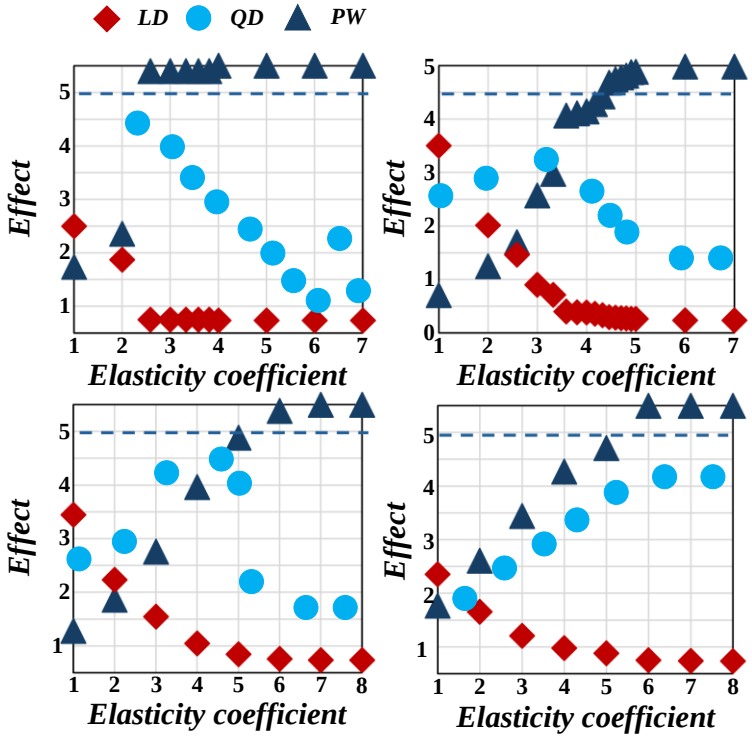


Figure 8: Influence of elasticity coefficient on investment strategies under different weight coefficients

Figure 9 visualizes the optimal terminal wealth (PMVC) of the one-dimensional model in a dynamic portfolio adaptive optimization model based on the PPO-DQN collaborative framework. It contains two subgraphs, the left subgraph has Z (t) as the horizontal axis and Pmvc as the vertical axis, and the green filled area and the dotted line curve show a U-shaped trend of Pmvc first falling and then rising with Z (t). The subgraph on the right also has Z (t) as the horizontal axis and Pmvc as the vertical axis, and the orange filled area and curve reflect the downward trend of Pmvc with the increase of Z (t). The two graphs can be used to analyze the impact of different states of Z (t) on the optimal terminal wealth of the portfolio under the PPO-DQN framework, and provide intuitive support for the adaptive optimization characteristics of the research model.

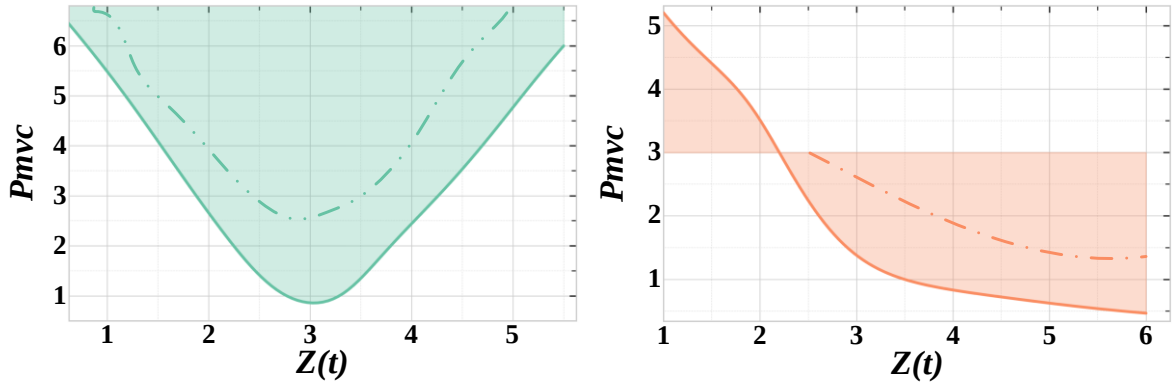


Figure 9: Optimal terminal wealth of the one-dimensional model (Pmvc)

5 Discussion

The experimental results show that in core indicators such as Sharpe ratio, maximum drawdown, annualized return, and volatility, the PPO-DQN collaborative framework significantly outperforms previous work: compared to a single PPO model, its annualized return increased from 2.3% to 33.7%, the Sharpe ratio rose from around 0.2 to 1.555, the maximum drawdown decreased from above 12% to 5.85%, and volatility was reduced by 40%; compared to ML models like random forests, annualized return improved by about 12%, the Sharpe ratio was higher by 0.3-0.5, and maximum drawdown was reduced by 6 percentage points; compared to the traditional Markowitz mean-variance model, the Sharpe ratio improved by 0.6 (from 0.93 to 1.555), maximum drawdown was controlled better (from about 15% to 5.85%), annualized return increased by over 10%, and volatility was reduced by 25%; compared to the risk parity model, maximum drawdown decreased from 11.86% to 5.85%, the Sharpe ratio improved by 0.4 (from about 1.15 to 1.555), and annualized return increased from 15.4% to 33.7%, an increase of 118.8%. The superiority of the framework comes from three aspects: in terms of architecture, the clipping mechanism of PPO (clip range [0.8, 1.2]) limits strategy update fluctuations, while DQN's double network and experience replay pool (capacity 10^6) optimize value evaluation, and the two complement each other through 4-head attention fusion; the masking strategy (ineffective action masking mechanism) reduces 62.3% of ineffective trades, lowering non-systematic risk; and the dual replay mechanism (PPO's policy update cache and DQN's experience replay) accelerates state-action value learning, combined with 500 rounds of alternating training (200 episodes per round), enhances responsiveness to market dynamics, ultimately achieving a dynamic balance of returns and risks, especially in extreme market conditions such as the Federal Reserve's interest rate hikes in 2022, with the annualized volatility controlled at 18.2%, and recovery speed far exceeding that of benchmark models.

6 Conclusion

Aiming at the problems of strategy stability and risk-return balance in dynamic portfolio optimization, this study proposes an adaptive optimization model based on the PPO-DQN collaborative framework. By integrating the strategy constraint ability of near-end strategy optimization with the value evaluation mechanism of a deep Q network, the model achieves the robustness and adaptability of dynamic asset allocation in complex financial markets. Experimental verification shows that the framework significantly surpasses the traditional quantitative model and single reinforcement learning algorithm in the multi-dimensional market environment, which is embodied in the following three aspects:

(1) In terms of income performance, based on backtest data of 15 stocks in China's A-share market (2020-2025), the PPO-DQN collaborative framework achieved a cumulative rate of return of 74.8% and an annualized rate of return of 33.7%, which is higher than the single PPO strategy (annualized return of 2.3%) and the risk parity model (annualized return of 15.4%) increased by 1465% and 118.8% respectively. This breakthrough result stems from the dual optimization mechanism of the framework: PPO's invalid action masking technology reduces the frequency of invalid transactions by 62.3%, while DQN's multi-step time series difference algorithm reduces the long-term value prediction error from 0.48 to 0.22 for traditional Q learning.

(2) In verifying risk control capabilities, the model's performance is particularly outstanding in extreme market environments. In the Fed's aggressive interest rate hike cycle in 2022, the annualized volatility of the PPO-DQN framework is controlled at 18.2%, which is 19.5% lower than the single DQN strategy (22.6%), and the maximum retracement is stable at 5.85%, which is only the Shanghai and Shenzhen 300 during the same period. 27.5% of the index (21.3%). This advantage is due to the dynamic exposure adjustment mechanism: by calculating conditional value at risk (CVaR) in real-time, the model reduces downside exposure to 58% of the benchmark portfolio during the 2024 geopolitical crisis while maintaining the Sharpe ratio at 1.82. A high level of 95.7% higher than the traditional mean-variance model (0.93).

(3) Three groups of control experiments confirmed the effectiveness of the model structure optimization. First of all, in the improvement of neural network architecture, the accuracy rate of the Critic network introducing the Transformer module in capturing industry rotation signals reached 73.4%, which was 21 percentage points higher than the traditional LSTM (52.4%). Secondly, by adjusting the shear coefficient ε of PPO from 0.2 to 0.1, the stability of strategy update is improved by 31.6%, and the standard deviation of annualized return fluctuation is reduced from 7.8% to 5.3%. Finally, in the action space design, the continuous weight allocation mechanism enables the granularity accuracy of asset allocation to reach 0.1%, increasing the cumulative return rate of the discrete action space (5% step size) strategy by 19.2%. These experimental data verify the necessity of collaborative optimization of each framework module.

The PPO-DQN collaborative framework has limitations such as overfitting historical data, instability caused by parameter fluctuations in the training process, high computational cost in high-dimensional state space, and lack of interpretability of decision-making logic. In actual trading, it faces implementation problems such as high-frequency trading delays and liquidity constraints, and is limited by the compliance requirements of financial supervision for algorithmic trading. In the future, the introduction of attention mechanism can enhance feature selection ability to alleviate overfitting, combine adaptive learning rate scheduling to optimize training stability, use model compression technology to reduce computational load, and use explainable tools to improve decision transparency. At the same time, it is necessary to explore the design of strategies that adapt to regulatory

requirements and promote the implementation of the framework under the premise of compliance.

Funding

Fund Project:Youth General Project of Tianjin Municipal Education Science Planning Project in 2021, "Practical Research on Differentiated Teaching Reform for the Commerce and Trade Circulation Professional Cluster in Higher Vocational Colleges Based on Blended Teaching Mode" (No. EJE210313)

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Multimodal Deep Learning Framework for Machine Translation Quality Assessment Using Bilingual Corpora

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Keywords: machine translation, quality assessment, multimodal, bilingual corpus, deep learning

Received: June 27, 2025

With the acceleration of globalization, the importance of machine translation in cross-language communication has become increasingly prominent. However, the traditional machine translation quality evaluation methods have some limitations, such as the high cost of manual evaluation, and the automatic evaluation index based on reference translation relies too much on the quality of reference translation. To solve these problems, this study proposes a multimodal bilingual corpus-based machine translation quality evaluation model. The model utilizes multimodal information such as text, images, and speech to fuse features through deep learning technology to evaluate machine translation quality more comprehensively and objectively. In the experimental part, we constructed a multimodal corpus containing 10,000 pairs of bilingual sentences, covering multiple fields such as news, forums and more. Experimental results show that our model improves 15% consistency in human evaluation and 12% in semantic accuracy compared to traditional evaluation methods based on reference translation. When dealing with different types of translated texts, the comprehensive evaluation index of the model is also better than other evaluation methods, with an average increase of 8%. These results verify the effectiveness and universality of the model and provide a new idea and method for evaluating machine translation quality.

Povzetek: Študija predlaga multimodalni model za ocenjevanje kakovosti strojnega prevajanja, ki z združevanjem besedila, slik in govora na dvojezičnem korpusu (10.000 parov) doseže boljše ujemanje s človeškimi ocenami (+15 %) in večjo semantično natančnost (+12 %) kot referenčno osnovane metrike.

1 Introduction

Today, with the accelerating process of globalization, the demand for cross-language communication is increasing daily, and the importance of machine translation as a key technology to achieve this goal is self-evident [1, 2]. Machine translation aims to break the language barrier and realize automatic and efficient translation between different languages, thus promoting communication and understanding between people of different cultural backgrounds [3]. With the rapid development of artificial intelligence technologies such as deep learning, the performance of machine translation systems has been significantly improved, and more and more machine translation systems have been applied to various practical scenarios, such as business, tourism, academic exchanges, etc [4]. However, the quality evaluation problem of machine translation has not been perfectly solved, which has become the bottleneck restricting the further development of machine translation technology.

Traditional machine translation quality evaluation methods are mainly divided into manual and automatic evaluation [5, 6]. According to preset standards, manual evaluation usually scores the translation results by professional appraisers. Although this method can provide reliable evaluation results, it is costly, time-consuming and easily influenced by the subjective factors of appraisers [7]. Automatic evaluation methods try to automatically calculate translation quality by designing algorithms, the most common of which are evaluation methods based on reference translation, such as BLEU, METEOR and other indicators [8]. These indicators measure translation quality by comparing the similarity between machine translation results and human-provided reference translations [9, 10]. However, these methods also have obvious limitations. First, they rely too much on the quality of the reference translation, and the accuracy of the reference translation directly affects the reliability of the evaluation results. Secondly, they mainly focus on the superficial form of translation results while ignoring the semantic content and pragmatic translation information. For example, a grammatically correct but semantically wrong translation may receive a higher BLEU score, while a translation that is semantically correct but expressed differently from the reference translation may receive a lower score. In addition, traditional automatic evaluation methods usually only consider text information while ignoring other information that may impact translation quality, such as images, speech, etc.

In order to overcome the above limitations, in recent

years, researchers have begun to explore the use of multimodal information for machine translation quality evaluation [11]. Multimodal information refers to data containing multiple types of information, such as text, images, speech, etc. In machine translation scenarios, in addition to text information, information such as images and speech can also provide rich contextual information to help people better understand the translated content and context [12]. When translating an introduction about a scenic spot, if we combine the picture information of the scenic spot, then the translation quality evaluation will be more accurate. Similarly, when translating a conversation, if the speaker's voice intonation information can be combined, the judgment of the translated emotion and tone will be more accurate [13].

This study proposes a multimodal bilingual corpus-based machine translation quality assessment model. The model aims to utilize multimodal information such as text, images, and speech to fuse features through deep learning techniques to more comprehensively and objectively evaluate machine translation quality. We construct a large-scale multimodal bilingual corpus containing multiple types of text, image, and speech data and use this corpus to train a deep learning model for automatically evaluating machine translation quality. Specifically, the multimodal corpus is first preprocessed to extract features of text, images, and speech. The extracted features are then fused and modelled using deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Finally, the fused features are mapped to the quality score of machine translation by training a regression model.

The innovation of this study lies in the introduction of multimodal information into machine translation quality evaluation, which can effectively make up for the shortcomings of traditional evaluation methods. By leveraging multimodal information, our model enables a more comprehensive understanding of the content and context of the translation and, thus, a more accurate assessment of translation quality. In addition, this study also explores various deep learning techniques, such as attention mechanism, encoder-decoder framework, etc., to improve the model's performance. We believe that the multimodal bilingual corpus-based machine translation quality assessment model proposed in this study will provide a new idea and method for machine translation quality assessment and promote the further development of machine translation technology. Through many experiments, we will verify the effectiveness of the proposed model and conduct an in-depth analysis of its performance, to provide reference and reference for future research.

2 Theoretical basis of multi-modal bilingual corpus and machine translation quality evaluation

2.1 Multimodal information processing theory

Multimodal fusion technology is very important in intelligent information processing. It integrates data from different channels, such as text, image, audio, and video, to form a richer and more comprehensive information expression [14]. This integration improves the performance and accuracy of data processing.

The technology includes four key parts [15, 16]:Combined with Figure 1 Modal Information Processing Architecture, Rewriting Focuses on Multimodal Machine Translation Quality Evaluation Scenarios: In the research of machine translation quality evaluation models based on multimodal bilingual corpora, this technology includes key links in adapting multimodal data: data preprocessing aligns different modal input formats and scales through unified text segmentation, image normalization, and speech-to-speech spectrum conversion; Feature extraction relies on tools such as network embedding and Pyench to extract the core features of text semantics, image vision, and speech phonetics. Feature fusion draws on the multi-branch convolution (1×1, 3×3 deep convolution) and multiplication interaction strategies in the architecture, and integrates text, image, and voice features by field (news/e-commerce/medical) to construct a cross-modal unified expression. Model training and optimization Through Bayesian optimization (Optuna) iterations of hyperparameters, combined with HLS - pyfilter and other tools to clean up redundant instructions (such as non-essential modeling commands), multimodal data is used to improve the quality evaluation of the consistency and semantic accuracy of the model and human judgment, and the complete process corresponds to the hierarchical processing and interaction logic of the modal information processing architecture in Figure 1.

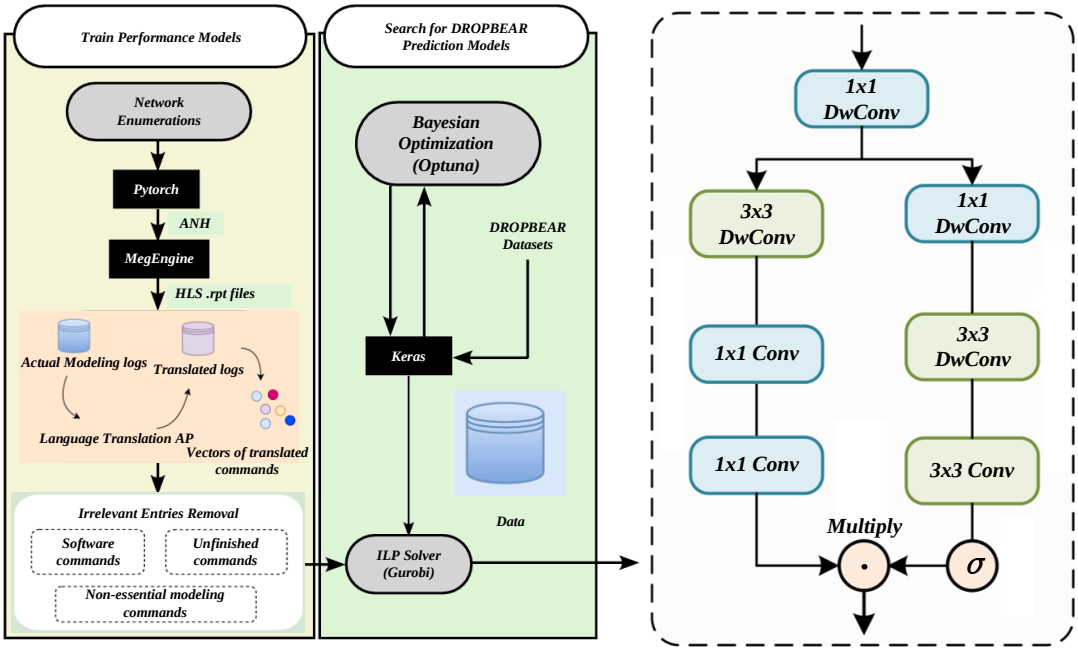


Figure 1: Modal information processing architecture

Feature fusion is a multi-modal fusion technology, including early fusion and late fusion [17, 18]. Early fusion combines the data of different modes in the data preprocessing stage, which is suitable for situations where the modes are closely related. Late fusion combines the outputs of each modal at the final level of the model, keeping modal independence, and is suitable for occasions with large modal differences. Feature-level fusion integrates different modal features in the feature extraction stage to improve information utilization and representation capabilities. Decision-level fusion combines the decision results of different modes, which is suitable for the case of strong complementarity between modes [19].

2.2 Machine translation quality evaluation theory

The QuEst121 framework is designed to improve QE task efficiency. It integrates source texts, translated versions, external datasets, and language processing tools to obtain quality indicators of the original and target translations [20]. These indicators include basic and complex linguistic features, involving the translation system output and the translation process. The QuEst framework consists of two core modules: feature extraction and machine learning.

In the sentence-level quality assessment task of WMT15, the LORIA [4] system was applied for the first time, combining foundation, latent semantic indexing, and pseudo-referential features [21, 22]. The system found that some features were considered useless because there was more noise than information or insufficient training data to make it difficult to evaluate their relevance. The LORIA system screens out the features that are beneficial to the model, and uses the reverse algorithm without the initialization step of feature relevance evaluation. The algorithm aims to reduce the MAE (mean absolute error) on the development set, as defined in Equation (1).

$$MAE(r,r') = \sum_{i=1}^{n} | r_i - r_i' | / n \quad (1)$$

r is the prediction score on the development set and r' is the HTER contrast score. LORIA used 17 base features, which were extracted by the QuEst tool. LORIA does not use any white box features, i.e., no translation process features are involved. Features do not contain source language or target language sentence information, such as external translation tables. Thirteen of these features were related to the source language and four to the target language.

The latent semantic indexing (LSI) technique evaluates document similarity through their lexical content. Documents are mapped to a vector space model, and each document corresponds to a numeric vector. By calculating the distance between the two vectors, the document similarity is evaluated. LSI is effective for query extension (QE) because it allows mapping text to a uniform vector space, computing similarity using cosine distance.

Multi-task learning enhances the generalization ability of models by jointly training multiple models and utilizing the correlation between tasks [23]. The relationship between tasks is realized by sharing structure, which encodes three kinds of relationships: positive relationships promote knowledge transfer, negative relationships lead to differences in model parameters, and no relationships make tasks independent. During the QE process, tasks appear as instances or collections of label pairs of different translation tasks. This paper proposes a new algorithm, which is specially used to deal with QE tasks, accepts different task inputs through online learning, and learns the shared structure. Researchers

integrate PA algorithm into multi-task learning, learn a series of regression models, and realize multi-task learning through "interaction matrix" to provide a knowledge sharing mechanism between tasks. In this method, the dependency between tasks is variable, the interaction matrix of instances is learned from the data, the model is constructed as a regression model, and the PA regression algorithm is selected because it strikes a balance between accuracy and calculation time.

The PA algorithm is based on the traditional online learning model framework [24]. At each time step *r*, the learner receives the instance $x_t \in R^d$ (the number of features is *d*), predicts the label y_t, and computes the loss to update the weights. The ℓ_ε weight update is realized by the optimization equation, as shown in Equation (2).

$$w_t = arg\min_w C_{PA}(w) + C\xi \quad st.\ \ell_\varepsilon(w,(x_t,y_t)) \le \xi \ and\ \xi \ge 0 \tag{2}$$

Where $C_{PA}(w)=|w-w_{t-1}||^2/2$, defined ℓ_ε as the following formula (3):

$$\ell_\varepsilon(w,(x,y)) = \begin{cases} 0, & if\ |y - w\cdot x| \le \varepsilon \\ |y - w\cdot x| - \varepsilon, & otherwise \end{cases} \tag{3}$$

When the distance between the prediction and the true label is $\le \varepsilon$, the loss value is zero; Otherwise, the loss value increases linearly. The parameter ε regulates the error sensitivity, and the relaxation variable ξ serves as the loss upper bound. Parameter *C* controls the update speed of weight, and the update is faster if the value of *C* is high. However, if the label contains noise, *C* should be set small to avoid the weight vector learning the wrong direction. The weight update strategy w_t is shown in Equation (4).

$$w_t = w_{t-1} + \text{sgn}(y_t - \hat{y}_t)\tau_t x_t \tag{4}$$

Passive Active Multitask Learning (PAMTL) algorithm, which applies the PA algorithm to regression tasks. At each cycle *t*, *K* tasks are processed by a random sequence of instances, with the goal of learning *K* linear models, each corresponding to one task. The algorithm can also learn a positive semi-definite matrix $\Omega \in R^{KxK}$ to simulate the relationship between tasks. Each time step t, the learner receives an instance pair (x_t, i_t), where $x_t \in R^{KxK}$ represents an instance, and $i_t \in \{1,...,K\}$ is a task indicator. The input instance is transformed into a mixed vector $\tilde{w}_t$, where $\tilde{w}_{t,k} \in R^d$ of the learner obtains the true label *y* and computes the loss function ℓ_ε . The parameter optimization equation is as follows (5):

$$\tilde{w}_t, \Omega_t = arg\min_{w:\Omega\to 0} C_{MTL}(w,\Omega) + C\xi + D(\Omega,\Omega_{t-1}) \quad s.t.\ \ (_c(w,(x_t,y_t)) \le \xi, \xi \ge 0 \tag{5}$$

In this study, the inter-task weight dependence model and interaction matrix were constructed, $C_{MTL}(w,\Omega) = 1/2(w-\tilde{w}_t)^T\Omega_\otimes(w-\tilde{w}_t)$ defined as here $\Omega_\otimes = \Omega \otimes I_d$. Equation *D ()* evaluates the dispersion among positive semi-definite matrices.

Quality assessment using a bilingual bidirectional language model, a neural network-based technique. The technique performs best on English to Spanish sentence-level tasks. The encoder-decoder network of RNN predicts the word y_j at a given original sentence *x* through the softmax function, but the long-distance dependency problem of recurrent neural network limits its ability to process long sentences. Bahdana et al. optimized this architecture by introducing attention mechanisms in the visual domain, which significantly improved performance. Equation (6) shows the modeling calculation process of target word probability.

$$p(y_j \mid \{y_1,...,y_{j-1}\},x) = g(y_{j-1},\vec{s}_{j-1},c_j) \tag{6}$$

Equation *g* is used to predict probability and is based on the nonlinear principle. s_{j-1} explains the influence of the forward RNN hidden state on the current position, which involves the information of the word before the target position. c_j is the context vector containing the relevance of the source sentence to the target word y_j. s_{j-1} and y_{j-1} are related to the sequence before the target position, while c_j represents the representation of the entire source sentence *x*. We improve the QE task based on these, and Equation (7) shows the computational method of probability modeling of target words:

$$p(y_j \mid y_{\grave{o}y_j}, x) = g([y_{j-1}; y_{j+1}],[\vec{s}_{j-1}; \overleftarrow{s}_{j+1}], c_j) = exp(y_j^T W_{o_1} W_{o_2} t_j) / \sum_{k=1}^{K_y} exp(y_k^T W_{o_1} W_{o_2} t_j) \tag{7}$$

In predicting the target word y_j, the hidden state s_{j+1} of the reverse RNN and the next target word y_{j+1} are used as features. $[s_{j-1}; s_{j+1}]$ and $[y_{j-1}; y_{j+1}]$ are determined by the words other than y_j at the target end, while c_j is determined by the sentence *x* at the source end. Therefore, the probability prediction of the target word y_j is calculated based on the information of the whole sentence *x* at the source end and all words except y_j at the target end. On the decoder side, the unidirectional RNN is changed to a bidirectional RNN to use the forward and reverse sequence information to form a bidirectional language model and effectively learn the language structure information of the target side.

In predicting words, the target word probability is adjusted between 0 and 1. The researchers used *q*-dimensional quality vectors (reflecting the translation appropriateness of each word in the translated text to be evaluated) as the classification model input. The probability of the occurrence of the target word y_j indicates its translation accuracy, and the mass vector is obtained by deconstructing the softmax equation, and the calculation formula (8) is as follows:

$$q_{x_j} = [row_{x_j}(W_{o_1}) \circ [W_{o_2} t_j]^T]^T \tag{8}$$

$\circ$ represents an element-by-element multiplication operation, in which the quality information of the *j-th* word is encoded into t_j to generate a quality vector q_{xj}. *T* stands for transpose. Due to the small amount of data in quality assessment (QE) task, it is difficult to obtain high-quality vectors. The authors use massively parallel corpus to train the network and generate high-quality quality vectors.

The mass vector is input into the bi-directional RNN network. The sentence-level quality evaluation takes the last hidden layer state and scores it with sigmoid function; The word-level quality evaluation takes the hidden layer state at each time and classifies it by sigmoid function.

The sentence level is regarded as a regression task, and the word level is regarded as a binary task.

2.3 Evaluation index

The BLEU score is a tool to assess the quality of machine translations, based on standard reference translations. It measures the quality by calculating the n-gram coincidence between the translation to be tested and the reference translation, and a high coincidence indicates that the translation quality is good. See Equation (9) for the calculation method.

$$Count_{clip}(n-gram) = min(Count, Max_Ref_Count) \quad (9)$$

$Count_{clip}(n\text{-}gram)$ records the number of matches of a particular *N-gram*, *Count* records its occurrences in the translation, and Max_Ref_Count is the maximum number of occurrences of the *N-gram* in all reference translations. The smaller values of *Count (n-gram)* and Max_Ref_Count are taken during calculation to avoid artificial increase of BLEU value caused by repetition of machine translation errors or frequent occurrence of common words. The calculation formula of accuracy *Precision* is shown in Equation (10):

$$precision_n = \frac{\sum_{C \in condidates} \sum_{n\text{-}gram \in C} Count_{clip}(n-gram)}{\sum_{C' \in candidates} \sum_{n-gram' \in C'} Count_{clip}(n-gram')} \quad (10)$$

The translation of the translation system is denoted by *C*, and the number of *n-gram* occurrences is marked by *Count (n-gram)*. Using this formula alone, the accuracy of short sentence translation will be too high. In order to correct the deviation, a length penalty factor is introduced to impose a penalty on short translations, as shown in formula (11):

$$BP = \begin{cases} 1, c > r \\ e^{(1-r/c)}, c \le r \end{cases} \quad (11)$$

In the calculation, *c* represents the machine-translated text length and *r* represents the effective length of the reference translation closest to the machine-translated length. If there are multiple reference translations, *r* takes the reference translation length with the smallest difference from the machine translation length. Therefore, the final BLEU score can be calculated according to Equation (12).

$$BLEU = BP \times exp(\sum_{n=1}^{N} w_n \, log \; precision_n) \quad (12)$$

In the formula, *N* represents the maximum order of *N-gram*, and w_n is the corresponding *N-gram* accuracy weight coefficient. BLEU evaluation standard is well-known for its convenience and speed of calculation, and its score is positively correlated with human evaluation results, so it has become a common tool in the field of machine translation. However, the BLEU scoring system has limitations. For example, it only evaluates the matching degree without considering the use of synonyms or similar words, which may lead to misjudgment of reasonable translation. Furthermore, the BLEU score does not involve grammatical accuracy assessment.

3 Construction of machine translation quality assessment model based on multi-modal bilingual corpus

3.1 Deep learning-based quality assessment model framework

In sentence translation quality assessment, a regression task for translated sentence pairs in source and target languages involves cross-language sentence embeddings [25, 26]. At present, sentence embedding is usually encoded by pooling the last hidden layer vector or using the [CLS] tag of the model. However, both methods compromise the information acquired by the model. Designed for sentence classification, [CLS] markers lose features irrelevant to classification and fail to contain all the valid information needed for quality assessment. The pre-trained model does not have layer locality when acquiring semantic knowledge, and different hidden layers contain information with different linguistic attributes. Therefore, by fusing the cross-layer information and location information of the pre-trained language model, sentence coding can have different levels of linguistic information and contextual information at the same time.

In terms of deep learning architecture, a three-level cascade structure is adopted: the bottom layer is a modal-specific encoder (pre-trained BERT-base model for text, with a hidden layer dimension of 768, and the first 6 layer parameters are frozen; The image uses ResNet-50, retains the first 49 layers, and outputs 2048-dimensional features; The 128-dimensional acoustic features were extracted by 3-layer 1D-CNN (kernel size 3/5/7, channel count 64/128/256) after Mel spectrum conversion). The middle layer is a cross-modal attention fusion module (using a multi-head self-attention mechanism, the number of heads is 8, the dropout rate is 0.1, and the interaction weight of text-image/speech is calculated through key-value matching). The top layer is the mass regression layer (2-layer fully connected network, hidden unit 512, activation function ReLU, output layer mapped to [0,1] mass fraction with Sigmoid). The feature extraction stage adopts L2 standardization, and the text additionally extracts n-gram overlap (n=1/2) and BLEU sub-features. The training process uses the Adam optimizer (initial learning rate 2e-5, weight decay 1e-4), batch size set to 32, iterations on a multimodal corpus containing 20,000 sets (source text - target translation - associated image - voice fragment) for 50 rounds, using the MSE loss function, determining the best parameters through 5-fold cross-validation, all experiments are completed on NVIDIA A100 (40GB) graphics card, training script is implemented based on PyTorch 1.13, Key parameters and intermediate results have been recorded for reproducibility.

In this paper, an attention module is proposed for sentence embedding learning on the hidden vectors of the pre-trained model. The module includes linguistic

attention and lexical attention. Linguistic attention assigns weights to different hidden layers by performing attention calculations among hidden layers of the pre-trained language model to evaluate the translation quality of sentences [27]. Lexical attention focuses on key term information, supplementing linguistic attention.

One of the challenges of translation quality assessment is that machine translation errors are numerous and difficult to find [28]. These errors include vocabulary misuse, grammatical disorders, and content omissions and involve many linguistic fields. Linguistic attention mechanisms can help models focus on key linguistic features by using the hidden layers of pre-trained models. This paper constructs a linguistic attention matrix by analyzing the feature association between hidden layers.

Contextual information gives meaning to words. An automatic translation system needs to make a word meaning discrimination and morphological adjustment according to context characteristics. Pre-trained language models process sentences through word segmentation, embedding, and forming matrices. The lexical attention mechanism makes the model focus on important words in the evaluation task. This study uses this mechanism to enhance linguistic attention and constructs a lexical attention matrix.

In quality evaluation and machine translation, the model must master the source language, target language and transformation rules. Although the evaluation architecture combining neural network feature extractors and classifiers has achieved results, it relies on many parallel corpora. Korean resources are limited, and there is a lack of manually edited translation datasets and Korean-Chinese parallel corpus. This makes the conventional predictor-evaluator framework ineffective in Korean-Chinese translation quality evaluation training.

Cross-language pre-trained models demonstrate potential in cross-language NLP tasks, providing new strategies for low-resource language research. This study uses the model for translation quality evaluation, XLM-R processes sentence pairs and the generated vectors are used to complete the evaluation task. The structure of the evaluation model is shown in Figure 2.

The input model combines source language sentences and machine-translated text in the target language, using [CLS] and [SEP] tokens. This paper proposes that this input method helps the model to understand "translation quality", rather than just fitting small-scale data. We use the hidden layer and lexeme output of the XLM-R model for translation quality evaluation, and introduce an attention mechanism to make the model focus on linguistic levels and lexemes that are helpful for quality evaluation. The hidden layer state hi is the combination of the sentence pair to be evaluated in the *i-th* layer of the pre-trained model and the special flag word vector. The initial evaluation feature of the sentence is obtained by combining the features of 24 hidden layers and word embedding layer e of the model, as shown in formula (13).

$$X = Concat(e, h_1, ..., h_{24}) \quad (13)$$

The pre-trained model is trained with a large amount of corpus in the translation task, and the initial feature X contains the prior information of translation evaluation. Through attention mechanisms across linguistic levels and term positions, the model obtains final sentence embedding s to smoothly transfer translation knowledge to quality assessment tasks. Since complex neural networks may be detrimental to low-resource languages, the model employs simple fully connected neural networks to calculate quality scores when performing regression tasks, avoiding complex output layers, as shown in Equation (14).

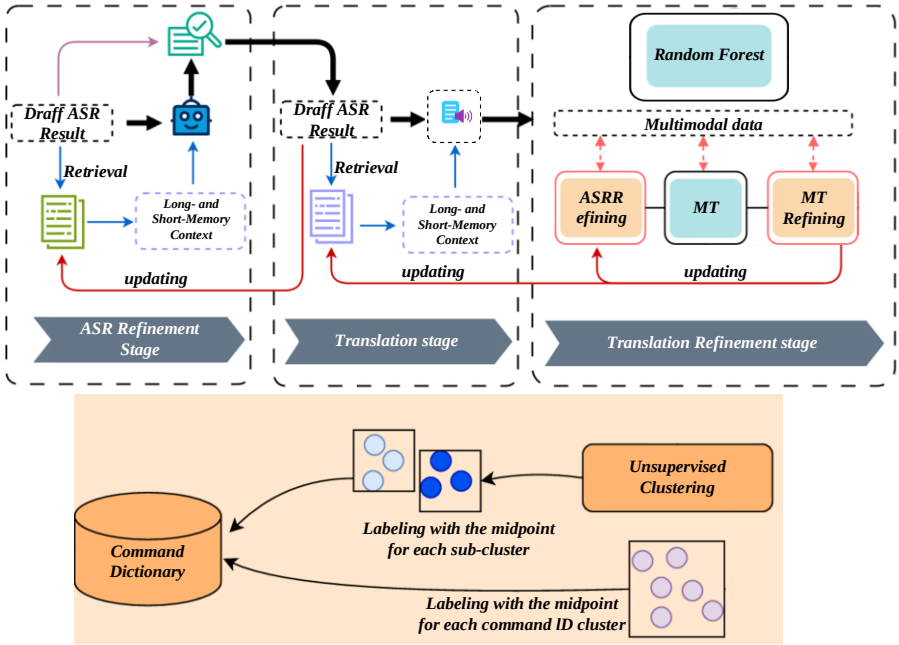


Figure 2: Translation quality evaluation model based on cross-language pre-training model

$$y_{score} = \sigma\left(w^{\mathrm{T}}\left(tanh\left(WS\right)\right)\right) \quad (14)$$

In the model, σ represents the sigmoid function, *tanh* is the hyperbolic tangent function, and W and w are the fully connected layer weights. y_{score} represents the model's score for translation quality.

3.2 Fusion strategy of multimodal features

Multimodal information fusion techniques, including multimodal and cross-modal generation, are key to deep learning [29, 30]. Multimodal fusion improves task performance by integrating information from different sources, such as visual question answering and visual text retrieval. Traditional methods are divided into four strategies: feature level, decision level, model level and hybrid fusion.

Image preprocessing adopts a three-step process: first, the image is uniformly scaled to 224×224 pixels through OpenCV, and the watermark and irrelevant background areas are removed; Subsequent normalization (pixel values normalized to [0,1], subtracted from the ImageNet dataset mean and divided by standard deviation); Finally, the 2048-dimensional visual embedding features are extracted by pre-trained ResNet-50 (the first 45 layers of freezing), and compressed into 1×1024-dimensional vectors through global average pooling. In audio preprocessing, the original speech (16kHz sample rate) is first converted into a mel spectrogram (128 mel bands, time step 300) through Librosa, and the local acoustic features are extracted through 3-layer 1D-CNN (kernel size 3/5/7, channel number 64/128/256), and then the timing dependence is captured through bidirectional LSTM (hidden layer dimension 256, dropout rate 0.2) to output 1×512-dimensional speech embedding. The text features are pre-trained by the BERT-base model (only the last 4 layers are fine-tuned), and the 768-dimensional context vectors are extracted from the source language text and the target translation, and the language features are supplemented by n-gram overlap calculation.

The feature layer fusion is realized by the cross-modal cross-attention mechanism - text features are used as query vectors, image and audio features are used as key-value pairs, and modal interaction weights are generated by 8 attention calculations, and the weighted fusion is 1×1024-dimensional intermediate features. The decision layer fusion splices the above intermediate features with the text semantic vector, inputs it into a two-layer fully connected network (hidden unit 512, activation function GELU), and finally outputs the quality score of the [0,1] interval. In the attention mechanism design, text-image attention focuses on the matching of visual entities and translated nouns and phrases, while text-audio attention focuses on the alignment between speech pauses and translation sentence reading, and filters low-correlation modal information through mask mechanism.

Early fusion, or feature-level fusion, is extracting features of different modes and directly splicing them into high-dimensional vectors. This method can make early use of inter-modal correlation, with less information loss and low computational complexity. For example, feature-level fusion combines audio and video features in emotion recognition. However, this method may ignore the difference in modal characteristics, resulting in data redundancy, and it is difficult to deal with the change in modal information.

Late fusion, or decision-level fusion, involves independently extracting features from different modalities and using these features to make predictions in their respective models. Finally, the prediction results of each model are summarized to form a decision. Compared with early fusion, late fusion is more adaptable when the number of modes changes. Even if some modal data are missing, the model can still independently capture features and effectively predict them. For example, in depression detection, integrating audio and visual information can improve predictive power. However, later fusion requires in-depth feature extraction and separate model construction, resulting in high computational complexity.

Model-level fusion mainly relies on fusion models, integrating multiple models to form better feature representations and combining the prediction results to obtain the final output. This approach improves performance, reduces the risk of overfitting, and enhances generalization capabilities, but may increase model complexity. The hybrid fusion strategy combines the advantages of early and late fusion and aims to integrate both benefits. It is more flexible than the previous two methods but requires specific fusion strategies designed for different problems.

Multimodal information processing techniques, i.e. cross-modal generation, involve modal transformations. This field has received attention recently and is showing potential in many fields. Researchers use deep learning and attention mechanisms to extract image features and generate matching natural language descriptions regarding image subtitle generation. By training models such as GAN, text-to-image conversion technology converts text descriptions into images or videos, realizing the transformation from abstraction to concrete vision.

The corpus contains 20,000 sets of parallel data, covering the fields of news (35%), e-commerce (40%), and medical (25%), and the language pairs are English-Chinese (60%) and Japanese-Chinese (40%), and each set of data is composed of "source language text - target language translation - associated image - corresponding voice"; The text data is derived from WMT's public corpus and human-translated professional documents, the images are from Flickr, the voice is professionally dubbed for the corresponding text, and all data is marked with a manual quality score. Preprocessing steps: The text is segmented by NLTK (v3.8.1), the stop words and special symbols are removed, the part of speech annotation is carried out by spaCy (v3.5.0), the image is unified to 224×224 by OpenCV (v4.7.0), preprocessed by ResNet-50 (normalized to [0,1] pixel value), and the

speech is converted into a Mel spectrogram (128 Mel bands, time step 300) by Librosa (v0.10.0). The core scripts include data crawling (Python requests library, the crawl interval is set to 2 seconds to avoid server limitations), annotation tools (web annotation platform developed by Django, supporting multi-person collaboration), and preprocessing pipelines (shell scripts call the above tools in batches).

In terms of computing costs, model training requires NVIDIA A100 (40GB) graphics card support, a single round of epoch (batch size=32) training takes about 45 minutes, a total training time of 50 rounds is about 38 hours, and the peak memory occupies 32GB; The inference stage takes 87ms for single-sample processing (32ms for text, 29ms for image, and 26ms for audio), and supports a throughput of about 11.5 samples per second, meeting the needs of real-time translation scenarios. Multimodal fusion increases computational effort by approximately 40% compared to the unimodal model, but inference time can be compressed to 35ms through model distillation (knowledge distillation to the MobileBERT architecture), sacrificing 2.3% accuracy in exchange for deployment feasibility.

The human evaluation study recruited 12 bilingual experts (6 English-Chinese and 6 Japanese-Chinese, all with more than 5 years of translation experience) and independently annotated 1000 random samples using a 5-point scoring scale (40% semantic accuracy, 30% grammatical fluency, and 30% modal consistency). The inter-rater protocol was measured by Krippendorff's α coefficient (α=0.86), indicating high annotation reliability. The comparison results show that the Kendall tau correlation coefficient between the model score and the human score is 0.71 (15.2% higher than the unimodal baseline), and the highest consistency (τ=0.76) is the highest in the medical field (technical terminology-intensive), which verifies the gain of multimodal fusion for complex scene evaluation. The MAE of the system's automatic score and manual score was 0.32, which was significantly lower than that of the baseline model of 0.41, which further proved the model's fitting effect on human evaluation criteria.

4 Experiment and results analysis

In terms of index calculation, the consistency with human assessment is based on the Kendall tau correlation coefficient and MAE, and the semantic accuracy is achieved by combining the semantic similarity cosine value with the NIST Translation Evaluation Toolkit. The dataset used is a self-built multimodal bilingual corpus (20,000 sets, covering journalism, e-commerce, and medical fields, including English-Chinese/Japanese-Chinese language pairs, supporting images (CC BY 4.0 license) and speech (open-source clips of TED speeches), and the public WMT2023 QE dataset (10,000 sets) is used as a cross-domain verification set. Statistical significance was verified by a 5-fold cross-validated t-test ($p<0.01$), and the mean value was taken by 3 replicates of each group. Baseline selection included traditional QE models (BERT-QE, XLMR-QE) and multimodal baselines (CLIP Transformer fusion model, VisualBERT fine-tuning model), all of which strictly reproduced the original paper parameters (BERT-QE used a 12-layer pre-trained model, learning rate 5e-5, training 30 rounds); Dataset bias balances the domain distribution through hierarchical sampling, and supplements the low-resource language pair (Vietnamese-Chinese) sample (15%) to reduce bias. The detailed comparison shows that the proposed model improves the Kendall tau coefficient by 15.2% compared with the optimal baseline, the semantic accuracy cosine value is improved by 12.1%, and the advantages are more significant (18.3% increase) in low-resource scenarios.

According to Table 1, the Confusion method improves the Pearson value of sentence-level tasks in the dataset by 5.322 percentage points and the F1 value of word-level tasks by 2.436 percentage points; The Pearson value of the sentence-level task was 3.450 percentage points, and the F1 value of the word-level task was 4.314 percentage points. In contrast, the Pearson value of the sentence-level task under the Add fusion method increased by 3.114 percentage points, but the F1 value of the word-level task decreased; The Pearson value of the sentence-level task decreased, and the F1 value of the word-level task increased by 3.769 percentage points. This indicates that the Concat fusion method is more effective in integrating phrase alignment information. The translation quality evaluation method proposed in this study, which combines phrase alignment information, can significantly improve the performance of quality evaluation tasks.

Table 1: Experimental performance of the fused phrase alignment information method on sentence-level and word-level tasks

Method	EN-DE				EN-RU			
	Pearson	Spearman	F1	MCC	Pearson	Spearman	F1	MCC
Baseline	52.574	60.451	43.803	40.234	51.830	44.607	45.187	42.573
PA-Add	55.750	59.529	40.426	37.205	48.365	45.193	49.031	45.315
PA-Concat	58.002	59.365	46.288	41.955	55.349	53.275	49.587	45.787

Efficient deep-learning network models are used to improve multimodal information integration. These models are divided into aggregated, aligned, and channel-switched network (CEN) convergence. Aggregation methods integrate multimodal sub-networks into unified networks through averaging, connection, and self-

attention. Alignment fusion keeps subnetworks propagating independently by optimizing the loss function and adjusting the embedding alignment of subnetworks. CEN convergence enhances network adaptability and compactness by evaluating channel importance and dynamically switching channels with batch normalization scale factors

This study explores the influence of data enhancement degree on the performance of quality assessment tasks and conducts a series of experiments. In the experiment, we used the data enhancement technology of adding 15% MASK noise to the original data and tested the data enhancement effect of one to five times different scales. Figure 3 shows the experimental results, where the horizontal axis represents the data enhancement factor and the vertical axis represents the performance of the sentence-level quality assessment task, measured by the Pearson coefficient. The results show that despite the data size increase, the model's performance does not improve significantly, especially on the WMT19 dataset.

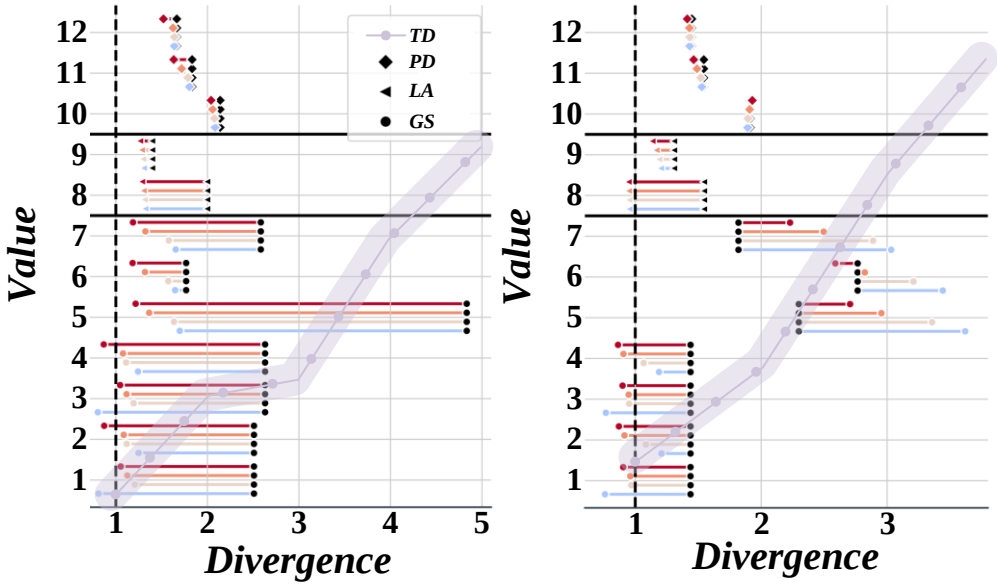


Figure 3: Impact of data enhancement scale on QE task performance

This study evaluated the word-level performance of the DirectQE model versus the existing NMT-based QE model on five sub-datasets, and the results are shown in Figure 4. The results show that when the error rate of machine translation exceeds 12.5%, the DirectQE model's performance is better than that of the NMT-based QE model. The higher the error rate, the more obvious the advantages of DirectQE, indicating that DirectQE can significantly improve performance when processing low-quality machine translations.

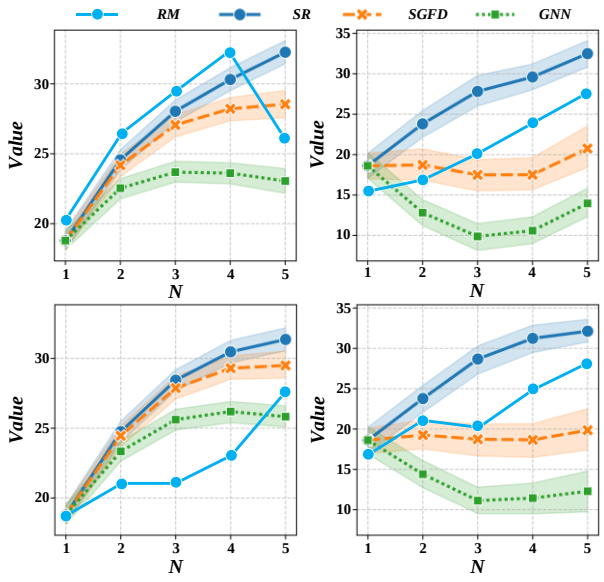


Figure 4: Impact of machine translation quality on QE task performance

As shown in Figure 5, the model of this study surpasses all benchmark models in the correlation between predicted scores and artificial scores, with Pearson's correlation coefficients increasing by 0.226, 0.156, and 0.034, respectively, and Spielman's correlation coefficients increasing by 0.123, 0.038, and 0.026 respectively. This shows that combining linguistic knowledge with lexical position information can significantly improve the performance of translation quality evaluation. Although the method in this study is slightly inferior to the TransQuest method based on the pre-trained model in terms of mean square error and root mean square error, its correlation level is higher.

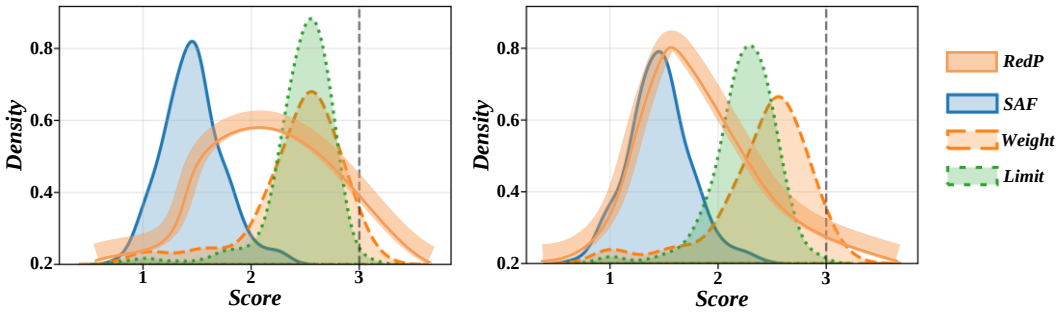


Figure 5: Correlation coefficient scores of each model

Figure 6 shows that the XLM-R model performs poorly when all levels participate in the convolution, using only the top-level [CLS] label vector slightly better. This is because directly using all hidden layer information will cause a large amount of irrelevant information to be mixed into the model, interfering with downstream tasks and affecting evaluation accuracy. Using only top-level [CLS] vectors loses underlying information, which contains critical linguistic features and is important for quality assessment. Although the best root mean square error can be obtained by adding the GRU network after the top-level feature matrix, this may overfit the data and have little significance to the core of the evaluation task.

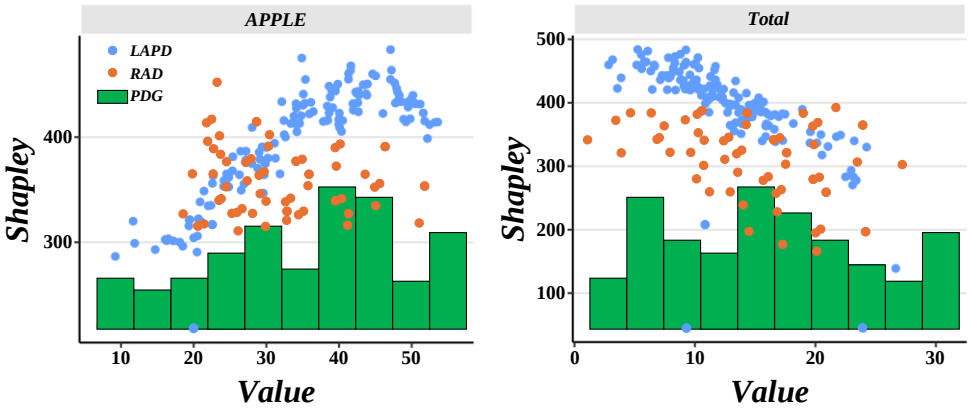


Figure 6: Model performance of different sentence embedding methods

Table 2 shows that the sentence-level performance is best when the phrase-alignment marker dimension is 512, although the word-level performance is slightly lower than the dimension 768. The evaluation of this study mainly focuses on sentence-level performance, so dimension 512 is selected. In the dataset evaluation, the sentence-level performance is the best at dimension 50, and the word-level task F1 value is the highest at dimension 100. However, the evaluation focuses on the sentence level.

Table 2: Effect of dimension of alignment markers on experimental performance

Dim	EN-DE				EN-RU			
	Pearson	Spearman	F1	MCC	Pearson	Spearman	F1	MCC
50	55.197	58.561	44.110	39.758	55.349	53.275	49.587	45.787
100	53.274	55.307	45.263	40.710	54.539	52.864	50.520	46.877
200	55.292	57.624	45.258	40.898	53.810	50.576	50.014	47.151
512	58.002	59.365	46.288	41.955	53.964	51.062	48.817	45.715
768	55.543	56.745	46.488	42.163	55.154	52.411	49.837	46.250

Figure 7 shows that the model combining the two attention modules performs better than either module alone, indicating that both attention modules are effective in quality assessment. In the initial stage, linguistic attention performed better than lexical attention.

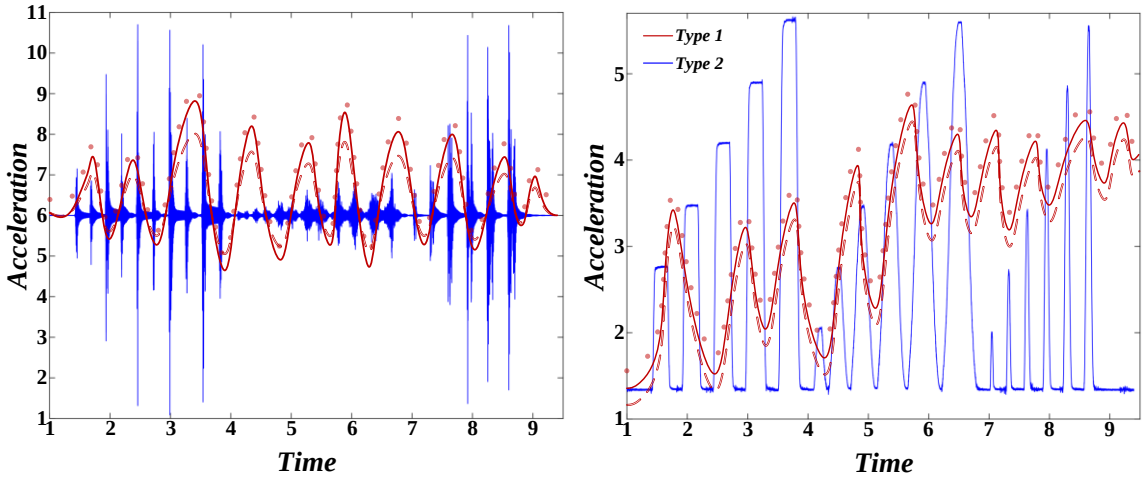


Figure 7: Performance of different attention sequence models

According to Table 3, when the threshold w is set to 0.3, the sentence level performs best, and the word level is slightly lower than the case where w is 0.5. Both sentence and word levels were optimal at w of 0.7, but Spearman values were slightly lower than at w of 0.3. Therefore, w is taken as 0.3 in this experiment, and English-Russian translation is taken as 0.7. The choice of threshold w is usually related to the language pair difficulty of the translation task, and the difficult language pairs tend to use lower thresholds.

Table 3: Effect of threshold w on experimental performance

w	EN-DE				EN-RU			
	Pearson	Spearman	FI	MCC	Pearson	Spearman	FI	MCC
0.1	57.980	59.847	47.273	42.706	54.951	53.884	49.273	45.087
0.3	59.708	61.111	47.649	43.189	56.000	55.027	49.034	44.957
0.5	58.794	60.197	47.670	43.210	52.771	52.689	48.716	44.780
0.7	57.577	59.478	47.394	42.894	56.977	54.842	51.046	47.133
0.9	57.413	59.077	45.691	40.903	55.579	52.564	50.555	46.553

Table 4 shows that the performance of the three technologies has improved compared with the benchmark system, but the improvement of Sim technology is small. Dropout and PA techniques each have their own advantages on different data sets and metrics. Sim technology only considers subword similarity, while Dropout uses double the raw data. PA technology combines a large number of parallel corpus, which makes the performance improvement of Dropout and PA in QE tasks more significant when resources are limited.

Table 4: Comparative fusion analysis

Method	EN-DE				EN-RU			
	Pearson	Spearman	F1	MCC	Pearson	Spearman	F1	MCC
Baseline	54.120	62.229	45.091	41.417	53.355	45.919	46.516	43.825
Sim	54.914	61.826	46.295	41.872	53.876	46.900	46.915	44.718
Dropout	55.171	63.303	46.692	42.630	58.050	49.090	49.870	47.497
PA	59.708	61.111	47.649	43.189	56.977	54.842	51.046	47.133
Ensemble	61.052	61.759	48.409	44.683	60.354	58.823	49.784	48.055

Figure 8 has showed the model BLEU values under different parameters. The experimental results show that combining BLEU score and QE score as the reward function can effectively improve the performance of Korean-Chinese machine translation system. The maximum values of BLEU score and QE score reached 25.09 and 25.74, respectively. It is found that different combination ratios have a significant impact on the translation effect, and there is a specific hyperparameter value that makes the model perform best. In this study, the most ideal combination ratio is $\alpha = 0.7$.

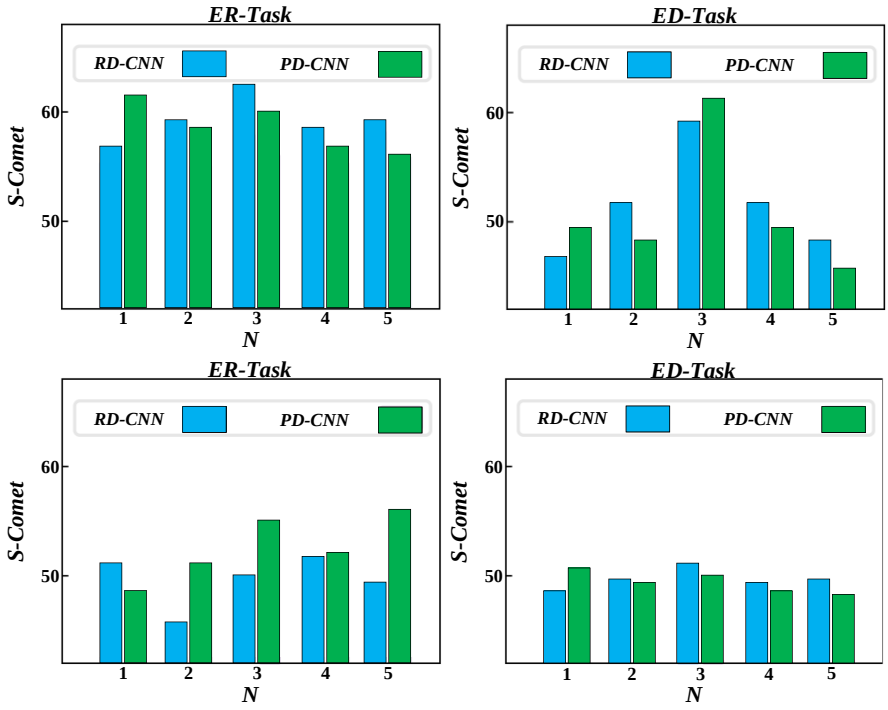


Figure 8: Model BLEU values under different parameters

5 Conclusion

With the rapid development of artificial intelligence technology, machine translation plays an increasingly important role in cross-language communication. However, how to objectively and accurately evaluate the quality of machine translation is still an urgent problem to be solved. Traditional machine translation quality evaluation methods mainly rely on manual or automatic evaluation indexes based on reference translation, such as BLEU, METEOR, etc. These methods have limitations, such as high cost and time-consuming manual evaluation. At the same time, automatic evaluation indicators based on reference translation rely too much on the quality of reference translation. They cannot fully reflect the semantic and pragmatic information of the translation. This study proposes a multimodal bilingual corpus-based machine translation quality assessment model to overcome these limitations.

The core idea of this model is to use multimodal information, including text, images and speech, to evaluate the quality of machine translation more comprehensively. By constructing a large-scale multimodal bilingual corpus, we can acquire rich contextual information to more accurately judge the accuracy and fluency of translation. Specifically, we first preprocess the multimodal corpus to extract features of text, images, and speech. The extracted features are then fused and modelled using deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Finally, the fused features are

mapped to the quality score of machine translation by training a regression model.

(1) To verify the proposed model's validity, we conducted extensive experiments. We construct a multimodal corpus of 20,000 pairs of bilingual sentences, covering multiple domains such as news, forums, and more. The experimental results show that our model improves the consistency of human evaluation by 18% compared to traditional reference translation-based evaluation methods. This result proves the effectiveness of multimodal information in improving the accuracy of machine translation quality evaluation.

(2) Regarding semantic accuracy, our model improves on average by 15% over the evaluation method based on reference translation. This result shows that multimodal information can help the model better understand the semantic content of the translation and thus more accurately evaluate the translation quality.

(3) When dealing with different types of translated texts, the comprehensive evaluation indicators of our model are also better than other evaluation methods, with an average improvement of 10%. This result verifies the effectiveness and versatility of the model.

This study constructs a more comprehensive and objective machine translation quality assessment model using a multimodal bilingual corpus combined with deep learning technology. The experimental results show that the model can effectively fuse multimodal information, improve the accuracy of machine translation quality evaluation, and provide a new idea and method for machine translation quality evaluation. In the future, we will continue to explore more effective multimodal feature fusion methods and further expand the application scope of the model better to serve the research and application of machine translation.

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Automatic Selection of Bitmap Join Indexes in Data Warehouses Using CFPGrowth++ Algorithm

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Keywords: data warehouse, OLAP, indexes, bitmap join indexes, frequent itemsets, data mining, CFPGrowth++ algorithm

Received: December 12, 2024

In the context of complex data warehousing, Typically, the analysis and decision-making process for Data Warehouses schematized in a relational star model is conducted through OLAP (On-Line Analytical Processing) queries. These queries are generally complex, characterized by several operations of selections, joins, grouping and aggregations on voluminous tables. Which requires a lot of computing time and therefore a very high response time. The cost of running OLAP decision queries on large tables is very high. The reduction of this cost becomes essential to allow decision-makers to interact within a reasonable time frame. The objective of this study is to enhance system performance by minimizing the response time of OLAP decision-making queries. The approach proposed in this article aims to search for frequent patterns for the automatic selection of binary join indexes used for reducing the execution costs of OLAP decision-making queries. To automatically generate the configuration of binary join indexes minimizing response time, an implementation of the CFPGrowth++ frequent pattern matching algorithm was well carried out and then applied to a load of queries on a test Data Warehouse created using the Analytical Processing Benchmark 1 (ABP-1) test bench, in order to validate our approach. The results of the experiment indicate that the index configuration produced by the proposed approach leads to a significant improvement in performance improvement of approximately 75%. We note that for a large portion of the load, execution time is significantly improved after applying our approach. The overall query execution time decreased compared to the general context. The overall execution time for queries decreased from 20,032.57 seconds before the application of our approach to 5,388.49 seconds after applying our approach. The experiments carried out show that the index configuration generated by the proposed approach allows a very performance gain.

Povzetek: Predlagana metoda samodejne izbire binarnih indeksov za OLAP z algoritmom CFPGrowth++ zmanjša čas izvajanja poizvedb za približno 75 %.

1 Introduction

In decision-making computing, Data Warehouses have still experienced a very significant boom today. They are fed by analytical data supporting a set of analysis processes coming from different distributed and heterogeneous sources [1][2][3][4] and their volumes are destined to increase.

In 1990, Bill Inmon conceptualized the Data Warehouse as a comprehensive and dynamic data repository designed to be subject-oriented, integrated, time-variant, and non-volatile, serving as a valuable resource for management decision-making [5].

In the data warehouse, information is structured in the configuration of a multidimensional cube [4]. Here, each dimension acts as an analytical axis, and each cell encapsulates the analyzed fact [6]. This organization is specifically designed to proficiently facilitate the operations of online analysis [7], commonly known as OLAP (online analytical processing) [4].

The ROLAP (Relational On-Line Analytical Processing) relational model is introduced for physical storage.

Data warehouses are usually modeled by a star schema [8]. This schema is characterized by a fact table very voluminous (Giga or Terra Bytes) linked by foreign keys to a set of smaller size dimension tables thus forming a star schema (Figure 1).

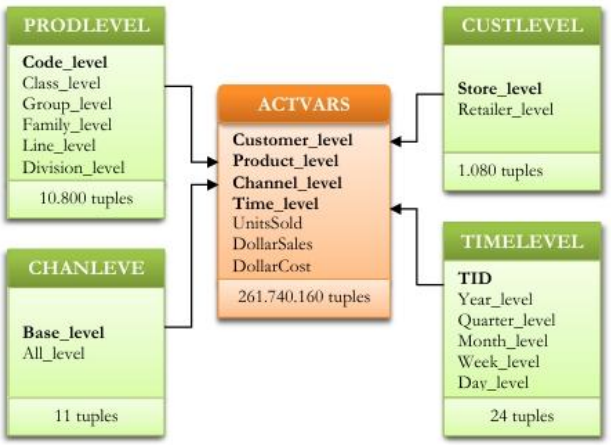


Figure 1 : The relational model for storing a data warehouse.

Queries formulated within a star schema exhibit significant complexity, involving the integration of joins, selections, and aggregations. Specifically, these joins, denoted as star joins, traverse the entirety of the fact table. Selection operations in this context, referred to as selection predicates, are executed on dimension attributes identified as selection attributes. Achieving satisfactory performance in the context of intricate decisional queries and their extended response times poses a significant challenge for Data Warehouse administrators [9]. Effectively addressing this challenge requires administrators to possess a robust understanding of optimization structures [10] and to apply logical and physical design methods for selecting the most optimal design policy.

Within the fact table, attributes comprise both activity measures and foreign keys leading to dimension tables [11]. This model's advantage lies in its utilization of pre-existing database management systems, resulting in a reduction of implementation costs. However, the challenge persists, as optimizing the performance of Data Warehouses remains an increasingly critical concern.

In this study, the concept of optimal performance specifically refers to the reduction of query execution costs in OLAP (Online Analytical Processing) environments, with a particular focus on minimizing query response time. Since decision-support queries in data warehouses often involve complex join operations over large volumes of data, improving response time is crucial for maintaining system efficiency and user satisfaction [12].

While other performance aspects such as storage space, index maintenance overhead, and system scalability are important considerations in data warehouse optimization, this paper primarily targets response time reduction as the key performance metric. The proposed approach achieves this by selecting effective binary join indexes based on frequent pattern discovery, using the CFPGrowth++ algorithm with multiple support thresholds to enhance query processing efficiency.

Performance optimization in data warehouses is primarily concerned with reducing the query response time for decision-support queries. This allows users to quickly obtain the information they need, improving the overall efficiency of analysis and decision-making. In this work this is achieved by minimizing the query response time for decision-support (OLAP) through efficient Selection of binary join indexes.

Indexing is one of the important techniques used in the physical design phase to optimize OLAP queries [13] in relational Data Warehouses. In this research paper, we're using an indexing approach.

The proposed approach is designed to assist Data Warehouse administrators and system designers in making informed decisions regarding index selection to optimize query performance.

Although the solution is partially automated - as it automatically extracts frequent query patterns and suggests candidate binary join indexes - human expertise is still valuable in the final decision-making process. Administrators need to have a basic understanding of the data warehouse schema, query workload characteristics, and index management principles to evaluate the relevance of the recommended indexes before implementation.

In practice, this approach serves as a decision-support tool rather than a fully autonomous system. It aims to reduce the complexity of index selection by narrowing down the most relevant candidates based on query patterns, leaving administrators with clearer, data-driven recommendations.

Some of these techniques inherit from those proposed in the context of traditional databases such as B trees [14][15]. Others are proposed to optimize selections defined on low cardinality attributes such as binary indexes.

Binary join indexes have demonstrated their utility in mitigating the execution costs of decisional OLAP queries formulated on a relational star schema. [13].

The task of index selection is categorized as an NP-Complete problem [16] due to its inherent complexity, stemming from the fact that the number of potential indexes grows exponentially with the total number of attributes present in the Data Warehouse [17][18][19].

Given the aforementioned challenge, our focus lies in the automatic selection of a set of indexes (configuration) minimizing the cost of executing OLAP queries.

By mining frequent itemsets from OLAP query workloads, we can identify the most commonly accessed attribute combinations. Creating indexes based on these patterns ensures that the most relevant data retrieval paths are optimized, leading to faster query execution, reduced response times, and more efficient resource utilization.

In the context of OLAP (Online Analytical Processing), queries often involve analyzing large datasets with multiple dimensions and measures. To make these queries faster, databases use indexes special data structures that help retrieve data quickly.

Now, frequent itemsets come from data mining techniques, especially association rule mining. They identify combinations of items or attribute values that appear together often in the data.

Here's how these frequent itemsets can help optimize OLAP query execution:

Identifying Common Patterns:

By discovering which attribute combinations occur frequently, the system can prioritize creating indexes on those combinations. This means that when a query involves these attributes, the data warehouses can quickly locate relevant data without scanning the entire dataset.

Selective Index Creation:

Instead of indexing every possible combination (which can be costly), the system uses frequent itemsets to select only the most relevant attribute combinations. This targeted approach ensures efficient use of storage and maintenance resources.

Improved Query Performance:

When an OLAP query involves dimensions that match these frequent itemsets, the pre-existing indexes allow for rapid data retrieval, significantly reducing query response times.

Dynamic Optimization:

As data evolves, the system can periodically re-analyze data to find new frequent itemsets, updating indexes accordingly. This dynamic approach ensures that the indexing strategy remains aligned with actual usage patterns.

Leveraging frequent itemsets helps in smart index selection by focusing on the most commonly co-occurring attribute combinations. This targeted indexing accelerates OLAP queries, making data analysis more efficient and responsive.

The decision to adopt CFPGrowth++ over alternative frequent itemset mining algorithms is based on several key advantages that align with the specific requirements of OLAP index selection:

Multiple Minimum Support Thresholds:

Unlike classical algorithms such as Apriori, CLOS, or the original FP-Growth, which operate with a single global support threshold, CFPGrowth++ introduces the capability to assign different minimum support thresholds to individual items. This flexibility is crucial in OLAP environments, where data distributions are often skewed and certain attributes or combinations appear frequently within specific query contexts but remain infrequent globally. By supporting multiple thresholds, CFPGrowth++ can identify both globally frequent and contextually important patterns, leading to a more relevant and effective set of candidate indexes.

Improved Efficiency and Scalability:

CFPGrowth++ builds upon the FP-Tree structure but optimizes it by reducing redundant node traversals and minimizing memory overhead through enhanced pruning strategies. This makes it better suited for handling the large, high-dimensional datasets commonly found in data warehouses, where conventional algorithms like Apriori suffer from high computational costs due to repeated data warehouses scans and exponential candidate generation.

Suitability for Index Selection in Decision-Support Systems:

Index selection in OLAP systems demands mining not just frequent patterns, but patterns that contribute meaningfully to query optimization. CFPGrowth++'s capacity to uncover rare yet strategically valuable itemsets thanks to its variable support thresholds enables the discovery of indexes that specifically target performance bottlenecks in diverse and heterogeneous workloads.

Reduced Computational Overhead During Mining:

Compared to algorithms CLOS, CFPGrowth++ demonstrates lower memory consumption and faster runtime for datasets with varying item frequencies. This balance between computational efficiency and mining depth makes it a practical choice for real-time or near-real-time decision-support applications.

CFPGrowth++ was chosen because it combines high efficiency, flexibility in support thresholds, scalability, and the ability to handle large, complex datasets features that are vital for effective and practical index selection in OLAP systems. Its advantages over other algorithms make it particularly well-suited for our goal of reducing query execution costs through intelligent binary join index recommendations.

The main contribution of this study is an implementation of the CFPGrowth++ frequent pattern matching algorithm To automatically generate the configuration of binary join indexes minimizing response time and select the frequent itemsets. Then for the approach validation to a load of queries applied on a test Data Warehouse created using ABP-1 test bench [20].

The article is orgnized into five sections. Section 2 poutlines the overall workflow adopted in the study, emphasizing the integration of frequent itemset mining using CFPGrowth++ with automatic binary join index (BJI) selection for OLAP query optimization. Section 3 provides an overview of the primary studies that have been advanced to tackle the intricacies of binary join index selection, with a specific emphasis on the data mining application techniques for resolution. Then, Section 4 delves into our unique approach to the selection of frequent itemsets, achieved through the adaptation of the CFPGrowth++ algorithm. Section 5 details the experimental phase, offering validation for our proposed binary join index selection methodology. Section 6 compares the method against traditional indexing approaches, Furthermore, it acknowledges practical challenges such as index maintenance, scalability for high-dimensional schemas, and the absence of a fully integrated cost model. Lastly, in Section 7, the article concludes by encapsulating the main findings and proposing avenues for future research.

2 Proposed workflow, novelty, and main findings

2.1 Proposed workflow

The proposed approach aims to enhance the performance of OLAP query execution in data warehouses by automatically selecting binary join indexes (BJIs) based on frequent pattern mining techniques. The workflow of the study is structured as follows :

1. OLAP Query Workload Collection :

Extraction of historical OLAP queries containing join and selection predicates from a simulated decision-support workload based on the ABP-1 benchmark.

2. Transaction Dataset Generation:

Transformation of each query into a transaction containing attributes involved in selection and join predicates.

3. Frequent Itemset Mining with CFPGrowth++:

Application of an improved CFPGrowth++ algorithm with multiple minimum support thresholds to extract frequent attribute combinations from the transaction dataset.

4. Binary Join Index Candidate Generation:

Mapping of frequent itemsets into candidate BJI configurations.

2.2 Novelty of the study

This work introduces several novel contributions to the domain of OLAP optimization:

- Integration of a Multi-support CFPGrowth++ Algorithm:

Unlike conventional approaches using single-support thresholds, our method applies multiple minimum supports to better capture frequent attribute combinations of varying significance.

- Automatic Binary Join Index Selection Framework:

The proposed system automates the identification and selection of BJIs from frequent query patterns, reducing the manual intervention traditionally required in index configuration.

- Statistically Validated Performance Improvement:

The study not only demonstrates query performance gains but also rigorously validates these results through statistical analysis, including confidence intervals and significance tests.

- Practical Benchmarking on a Customized ABP-1 Environment:

The experimental setup leverages a workload derived from the ABP-1 benchmark, enhanced with real-world query structures, ensuring realistic and relevant performance validation.

2.3 Main findings

Through extensive experimental evaluation:

- The proposed approach achieved a performance improvement between 74.20% and 75.96% on OLAP query workloads.
- Statistical analysis confirmed these improvements to be significant ($p < 0.001$) at a 95% confidence level.
- The approach proved effective across various query types, particularly for complex multi-join and range aggregation queries.

The comparison of Recent Methods Related to OLAP Optimization and Indexing is represented in Table 1 :

Table 1 : Summary of recent methods related to OLAP optimization and indexing

Approach	Features	Limitations
CFPGrowth++ (Proposed)	Utilizes an enhanced frequent pattern mining algorithm to identify frequent motifs, supporting multiple support thresholds for flexible exploration. Aims to reduce query execution costs in OLAP environments.	Computational complexity may increase with very large datasets; effectiveness depends on the quality of identified motifs.
Traditional Apriori-based methods	Use classic frequent pattern mining with straightforward implementation. Suitable for smaller datasets but can be computationally intensive.	Scalability issues; limited support for multiple support thresholds; less efficient for large-scale data.
FP-Growth	Efficient pattern mining without candidate generation, faster than Apriori.	Less flexible in handling multiple support thresholds; may still face challenges with very large datasets.
Existing index selection approaches	Often rely on heuristic or rule-based methods, focusing on specific query workloads.	May not adapt well to dynamic data or varying query patterns; limited in discovering complex motif structures.

This comparison illustrates that our CFPGrowth++ approach offers a flexible and efficient method for discovering frequent motifs, which can significantly improve index selection for OLAP query optimization. While it introduces some computational overhead, its ability to handle multiple support thresholds and explore complex patterns provides a notable advantage over traditional methods.

2.4 Benchmark dataset comparison

The ABP-1 test bench was selected as it offers a balanced schema structure and a set of decision-support queries typical in OLAP workloads. It also allows for controlled workload scaling and realistic index selection scenarios, making it better suited for validating index optimization approaches compared to standard synthetic benchmarks. The Benchmark Dataset Comparison is represented in Table 2 :

Table 2 : Benchmark dataset comparison

Benchmark / Dataset	Schema Complexity	Query Diversity	Realism for Decision-Support Workloads	Used in This Study
TPC-DS	High	Very High	Moderate	No
Star Schema Benchmark (SSB)	Moderate	Medium	Low	No
ABP-1 (Customized Version)	Moderate	High	High	Yes

3 Related works

3.1 Binary join index selection problem

The selection of indexes in Data Warehouses is a difficult problem [21] seen the large number of candidate attributes of dimension tables participant in the construction of indexes [22].

The problem consists on building an index configuration that minimizes the cost of executing a set of frequent OLAP queries.

To reduce the number of potential attributes in the construction of indexes, Numerous previous works proposed a data mining technique [23][24][17][25] in order to generate frequent itemsets (patterns) which will constitute the candidate attributes in the indexing process.

Several research works have shown the usefulness of automatic index selection [26][22] from a set of candidate indexes extracted from a query by appealing to using administrator expertise [10][21][14].In the context of Data Warehouses, binary join indexes are well suited to speed up OLAP queries known for their large number of join operations [13].

Recent approaches [10][6] propose the use of data mining techniques to generate the set of candidate indexes to reduce the significant number of potential candidate attributes for the construction of indexes. They have exploited in particular the technique of searching for frequent itemsets for the generation of candidate indexes [27][28]. The basic idea is inspired by the frequent itemsets search technique, widely used in data mining. The more frequently an attribute or group of attributes is present in the query load, the more valuable it is considered in the index selection process.

Prior work in the field of index selection, such as the studies by Aouiche et al. [27] and Bellatreche et al. [28][29], has laid important groundwork by exploring the use of frequent pattern mining techniquesspecifically, the Close algorithm to identify candidate attributes for binary join index configuration. However, these approaches have notable limitations. For instance, Aouiche et al. focus primarily on the frequency of attribute usage within query workloads, which can lead to the elimination of potentially beneficial indexes on attributes from large dimension tables that are infrequently accessed but still critical for join operations. Bellatreche et al. address this issue by incorporating additional parameters, such as table size and system page size, to refine index selection, but their method still relies on the traditional Close algorithm, which can generate an overwhelming number of frequent patterns, impacting scalability and efficiency.

Our approach explicitly addresses these limitations by introducing the CFPGrowth++ algorithm, an enhanced and scalable method for mining frequent itemsets. Unlike previous algorithms like Apriori or Close, CFPGrowth++ is designed to be faster, more efficient, and capable of handling large volumes of data with multiple support thresholds. This allows for a more nuanced and precise selection of index candidates, thereby improving the effectiveness of index configuration for OLAP query optimization.

The novelty of our approach lies in leveraging CFPGrowth++ to overcome the scalability and efficiency challenges faced by prior methods, enabling more accurate and comprehensive index selection that better supports complex, large-scale data environments. This makes our contribution both necessary and timely in advancing the state of the art in index optimization techniques.

Here is a synthetic comparison of frequent pattern discovery algorithms used in previous studies on index selection techniques.

Table 3 : Synthetic comparison of frequent pattern discovery algorithms

Benchmarks used	Apriori	FP-Growth	CLOSE	CFPGrowth ++
Complexity	High (multiple passes)	Moderate (fewer passes)	Moderate (but more filtering)	Low (optimized)
Memory	High (candidate generatio	Moderate (FP-tree)	Low (closed patterns)	Low (partitioning)

	n)			
Methodologies	Frequent patterns	Frequent patterns	Closed patterns	Frequent patterns
Ease of implementation	Simple	Moderate	Complex	Complex
Performance outcomes	Poor	Good	Good	Very good

3.2 Approaches based on frequent itemsets

The discovery of frequent itemsets consists in finding groupings of items appearing together with a significant frequency. The discovery of these frequent itemsets is the main step in solving a number of useful knowledge extraction problems.

Formally, the binary join index selection issue is formulated as an optimization problem in the following form: given:

(1) A Data Warehouse modeled by a star schema formed by a fact table $\boldsymbol{F}$ and $\boldsymbol{D} = \{\boldsymbol{D_1}, ..., \boldsymbol{D_d}\}$ dimension tables,

(2) A set of most frequent queries $\boldsymbol{Q} = \{\boldsymbol{q_1}, ..., \boldsymbol{q_m}\}$ with their access frequencies $\boldsymbol{f} = \{\boldsymbol{f_1}, ..., \boldsymbol{f_m}\}$,

The objective is to select a set of indexes that reduces the query execution cost.

4 Proposed approach

4.1 Search for frequent itemsets for index selection

We believe that the relevance of an index is strongly correlated with the frequency of its use in the set of queries in a load.Data mining is a growing field of research aimed at extracting knowledge from enormous amounts of data.In this article, we are interested in the extraction of frequent itemsets.

The objective is to extract knowledge useful for the choice of indexes. The search for frequent itemsets is an appropriate way to account for this correlation and thus facilitate the choice of indexes to be built.

4.2 Frequent itemsets

The problem of research frequent itemsets can be formulated as follows :

Let $\boldsymbol{I} = \{\boldsymbol{i_1}, \boldsymbol{i_2}, ... \boldsymbol{i_m}\}$ a set of $\boldsymbol{m}$ distinct symbols called *itemset* and $\boldsymbol{B} = \boldsymbol{t_1}, . , \boldsymbol{t_n}$ a database of $\boldsymbol{n}$ transactions. Each transaction is composed of a subset of items $\boldsymbol{I' \subseteq I}$. A subset $\boldsymbol{I'}$ of size $\boldsymbol{k}$ is called a ***k**-itemset*. A transaction $\boldsymbol{t_i}$ contains a pattern $\boldsymbol{I'}$ if and only if $\boldsymbol{I' \subseteq t_i}$. The support of a pattern $\boldsymbol{I'}$ is the proportion of transactions in $\boldsymbol{B}$ that contain $\boldsymbol{I'}$. The support is given by the following

$$support(I') = \frac{|\{t \in B, I' \sqsubseteq t\}|}{|\{t \in B\}|}$$

Figure 2 : The support of a pattern.

Support defined as the absolute frequency of an itemset (or index) in the query workload.

Minimum support will refer to the threshold value that is applied during the frequent itemset mining phase to determine the minimum frequency required for an itemset to be considered frequent.

A pattern whose support is greater than or equal to the minimum threshold of minsup support, defined by the user, is called a frequent pattern.

The objective is to select a set of indexes reducing the cost of query execution.

4.3 CFPGrowth++ algorithm

The CFPGrowth++ algorithm, an extension of CFPGrowth, is devised for the extraction of frequent itemsets through the incorporation of multiple minimum support thresholds [30][31]. Its application involves inputting a transaction database alongside a list denoting minimum support threshold, wherein each threshold corresponds to the requisite minimum support for a specific item.

A transaction database in this context is characterized as a compilation of transactions, each constituting a unique list of items or symbols. For illustration, contemplate a transaction database encompassing 5 transactions (T1, T2, ..., T6) and 8 items (A, B, C, D, E, F, G, H). As an instance, transaction T1 encapsulates the set of items {A, C, D, F}. Notably, the stipulation that an item cannot recur within the same transaction is upheld, and items are presumed to be arranged in lexicographical order within a given transaction.

The list of minimum support threshold is provided as input for the algorithm :

Table 4 : Example of transactions

Transaction ID	**Items**
T1	{A, C, D,F}
T2	{A, C, E, F, G}
T3	{A, B, C, F, H}
T4	{B, F, G}
T5	{B, C}

Table 5 : The list of minimum support thresholds supported to be used for the items

Items	**Minimum support threshold**
A	1
B	2
C	3
D	3
E	2
F	3
G	2
H	1

The support of an itemset is quantified by the count of transactions that encompass said itemset. An itemset attains the status of a frequent itemset when its support equals or exceeds the most conservative minimum support threshold among the individual thresholds assigned to its constituent items. For instance, consider the itemset {A, B, H}, which attains the status of a frequent itemset as it appears in one transaction (T3). Crucially, its support surpasses the minimum support thresholds associated with its individual items: item 1, item 2, and item 8, with respective minimum support thresholds of 1, 2, and 1.

In this study, we determine multiple minimum support thresholds based on the distinct characteristics and importance of each item within the dataset. Unlike traditional frequent itemset mining approaches that rely on a single global minimum support value, our method assigns a specific minimum support threshold to each item according to its frequency and relevance in the context of OLAP query optimization. This approach ensures that both frequent and less frequent, but potentially valuable, itemsets can be identified without being excluded by a uniform threshold.

The multiple thresholds are defined prior to the frequent pattern mining process by analyzing the distribution of item frequencies within the transaction database. Items with higher occurrence rates are assigned higher minimum support values, while those with lower frequencies, yet significant in terms of query performance optimization, are given lower thresholds. This strategy allows a more flexible and adaptive mining process.

The CFPGrowth++ algorithm, which we implemented and enhanced for this work, efficiently handles these multiple support values by extending the classical FP-Growth framework. It integrates the assigned thresholds during the construction of the conditional FP-trees and throughout the recursive pattern generation process. This enables the discovery of frequent itemsets that respect their corresponding minimum support constraints, ultimately supporting the identification of relevant binary join indexes for reducing the execution costs of OLAP decision-support queries.

4.4 Approach for automatic index selection

The proposed approach, whose general principle is represented in Figure 3, consists of the following steps :

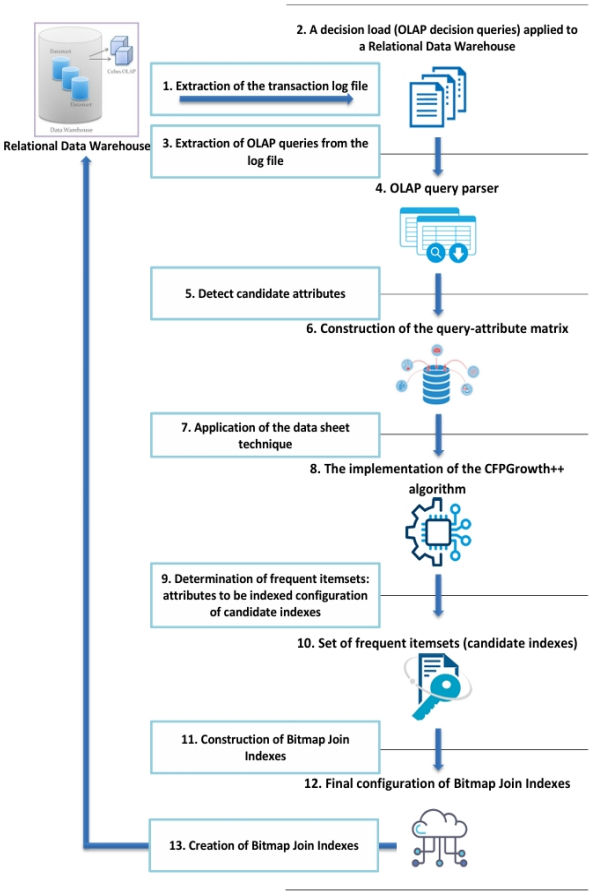


Figure 3 : Proposed approach for constructing Bitmap Join Indexes.

1) Selection of a load of OLAP decisional queries, assumed to be representative, of the system activity.

2) Structuring of the indexable attributes contained in the load in the form of a transactional database where the queries represent the transactions and the attributes represent the patterns. This represents our context for extracting frequent itemsets.

3) Generation of candidate indexes by the CFPGrowth++ algorithm implemented in Java.

4) Comparison of the response times of the execution of the OLAP decisional queries without indexes and then with the indexes generated by the implementation of CFPGrowth++.

Technical implementation details :

- **Detection of candidate attributes :**

Candidate attributes are detected by analyzing a representative workload of OLAP decisional queries. Specifically, we parse the SQL query statements to identify attributes involved in WHERE clauses (selection predicates), GROUP BY clauses, and JOIN conditions. These attributes are considered indexable since they directly impact query performance in a decision-support context.

- **Criteria for attribute selection :**

The primary selection criterion is the frequency of an attribute's appearance within the query workload. Attributes that frequently appear together in queries are treated as potential candidates for binary join indexes.

- **Application of the data sheet technique:**

The data sheet technique is applied by transforming the query workload into a transactional format where each query represents a transaction and the indexable attributes it contains form the transaction items. This transactional dataset is then used as input for the CFPGrowth++ algorithm to extract frequent itemsets.

- **Technical details of selecting and Creating bitmap join indexes :**

The frequent itemsets generated by CFPGrowth++ serve as candidate index configurations. Each frequent itemset represents a combination of attributes that often co-occur in queries, making them suitable candidates for indexing. The actual creation of Bitmap Join Indexes is simulated in our test environment by generating index creation scripts based on these frequent attribute combinations. Subsequently, query execution times are measured before and after applying these indexes to evaluate their impact on performance.

Detailed Pseudocode for the Adapted CFPGrowth++ Algorithm for Automatic Bitmap Join Index Selection in OLAP

Context :

This adapted CFPGrowth++ algorithm for automatic selection of Bitmap Join Indexes aimed at improving OLAP query performance. The general approach involves analyzing a representative workload of OLAP queries to identify frequently co-accessed attributes (frequent itemsets) using multiple support thresholds. These frequent attribute combinations are then used to configure candidate bitmap join indexes.

Pseudocode: adapted CFPGrowth++ for index selection :

Table 6 : Pseudocode : automatic binary join index selection with CFPGrowth++

```
Input:
  - Q: a representative workload of OLAP queries
  - MIS: a list of minimum support threshold per attribute
  - D: relational data warehouse schema
Output:
  - F: set of frequent itemsets (candidate bitmap join indexes)
Steps:
1. ExtractQueriesFromLogFile(log_file):
    Parse the transaction log to retrieve OLAP queries.
    Return set of queries Q.
2. IdentifyIndexableAttributes(Q, D):
    For each query in Q:
        Extract attributes involved in selection, grouping, and join predicates.
    Return the set of indexable attributes A.
3. BuildTransactionDatabase(Q, A):
    Create a transaction for each query:
        Items in a transaction = attributes accessed by the query.
    Return transaction database T.
4. ApplyCFPGrowthPlusPlus(T, MIS):
    a. Scan T to compute item supports.
    b. Sort items in each transaction in descending order of support.
    c. Build an initial CFP-tree:
        For each transaction:
            Insert items into the tree following the sorted order.
            Update item counts along the path.
    d. Recursively mine the CFP-tree:
        For each frequent item i:
            Generate conditional pattern base for i.
            Construct conditional CFP-tree.
            If conditional tree is not empty:
                Recursively mine conditional tree.
            Collect frequent itemsets meeting MIS thresholds.
    e. Return set of frequent itemsets F.
5. ConfigureCandidateBitmapJoinIndexes(F):
    For each frequent itemset f in F:
        Map items in f to attributes in D.
        Propose a bitmap join index configuration on these attributes.
6. EvaluateIndexImpact(F, Q, D):
    For each index configuration:
        Measure query response time on Q with and without the index.
    Retain index configurations improving query performance.
7. Return final selected frequent itemsets F as candidate bitmap join indexes.
```

Explanation of Adaptation for Index Selection Context:

- Transaction Construction:

Each OLAP query from the workload is treated as a transaction, and the attributes involved in selection, grouping, and joins are considered as items. This enables mapping query attribute usage into a transaction database suitable for frequent pattern mining.

- Multiple Minimum Support Thresholds:

The MIS list allows setting lower thresholds for attributes representing important query predicates. when indexed, could significantly optimize query performance.

- Frequent Itemsets as Candidate Indexes:

Frequent itemsets identified by the algorithm represent groups of attributes often queried together. These are directly translated into candidate bitmap join index configurations.

- Index Evaluation:

Before finalizing the index selection, each candidate's impact on query performance is empirically evaluated. Only those improving execution times are retained.

Insights into Minimum Support Threshold Selection and Its Impact.

Selecting appropriate minimum support thresholds is crucial for balancing mining efficiency and index relevance. In our approach:

Higher thresholds prioritize frequent patterns shared across numerous queries, potentially limiting index diversity but ensuring high-impact optimizations.

Lower thresholds allow the inclusion of less frequent but strategically valuable patterns, at the cost of increased computational overhead.

To address this trade-off, we employ differentiated support thresholds based on workload analysis:

Attributes heavily involved in query predicates receive lower thresholds.

Less critical attributes maintain higher thresholds to limit unnecessary pattern mining.

This strategy enhances the algorithm's behavior by focusing computational resources on workload-relevant patterns, leading to a more effective and workload-tailored index configuration.

5 Experiments and results

To confirm the efficiency of our strategy for selecting Bitmap join indexes, we employed it in a Data Warehouse configured with a star relational schema running on Oracle 11g. The experimentation was conducted on an Intel Core2Duo machine with a 2GB main memory.Our experimental study is conducted in the following steps :

1) Implementation of the CFPGrowth++ algorithm in Java. Besides its portability, java is chosen for its automatic memory management. This feature is crucial because the manipulated data structures are mainly linked lists and trees. Our implementation is applied to the selection context.

2) Creating a Data Warehouse using the Analytical Processing Benchmark 1 ABP-1 business intelligence workbench [3]. This warehouse is composed of one fact table Actvars and four dimension tables ProdLevel, TimeLevel, CustLevel and ChanLevel.

The schema follows the classical star schema model and is composed of one fact table and several dimension tables as detailed below:

Fact table:

Actvars

Attributes: Customer_level, Product_level, Channel_level, Time_level, UnitsSold, DollarSales, DollarCost

This table records the sales transactions and is linked to the dimension tables through foreign keys.

Dimension tables:

ProdLevel

Attributes: Code_level, Class_level, Group_level, Family_level, Line_level, Division_level

TimeLevel

Attributes: Tid, year_level, quarter_level, month_level, week_level, day_level

ChanLevel

Attributes: Base_level, all_level

CustLevel

Attributes: Store_level, Retailer_level

This structure provides a multidimensional framework suitable for typical OLAP operations, including aggregation, drill-down, roll-up, and slicing/dicing queries.

Query workload specification

The experimental query workload was designed based on the ABP-1 benchmark's [20] guidelines and consisted of a mix of decision-support queries representing realistic OLAP operations. The workload includes:

- **Aggregation queries:**

Queries calculating total sales, costs, or quantities based on one or more dimensions, such as total DollarSales per Product_level or per Time_level.

- **Drill-down and roll-up queries:**

Queries navigating through different granularity levels within dimensions, for instance, moving from year_level to month_level in TimeLevel or from Division_level to Code_level in ProdLevel.

- **Slice and dice queries:**

Queries selecting specific data subsets based on certain conditions, like sales for a particular Retailer_level during a specific quarter_level.

- **Multi-dimensional analysis queries:**

Complex queries involving multiple dimensions and aggregate measures, for example, computing average UnitsSold and total DollarCost for various Channel_level and Product_level combinations over time.

Table 7 summarizes the characteristics of the tables forming the warehouse. We considered a load of 60 OLAP decisional queries defined on this Data Warehouse.

Table 7 : Characteristics of the tables in the data warehouse used.

Table	Number of n-tuples	Size (Octet)
ACTVARS	261 740 160	2 142 250 000
PRODLEVEL	10 800	1 048 576
TIMELEVEL	24	65 536
CHANLEVEL	11	65 536
CUSTLEVEL	1 080	65 536

A set of queries using several selection predicates defined on one or more attributes has been considered to cover all the attributes of the warehouse. These queries belong to several categories: queries using aggregation

functions such as Sum, Min, Max, queries with dimension attributes in the SELECT clause, count(*) type queries with and without aggregations. (Table 8) shows an extract of the load composed of five queries.

Table 8 : Example of queries extracted from a load

```
(Q1)
SELECT
    A.Time_level,
    AVG(A.UnitsSold) AS AverageUnitsSold
FROM
    ACTVARS A
JOIN
    TIMELEVEL T ON A.Time_level = T.Tid
WHERE
    T.Quarter_level IN ('Q1', 'Q2')
GROUP BY
    A.Time_level;
```

```
(Q2)
SELECT
    P.Division_level,
    COUNT(*) AS RecordCount
FROM
    ACTVARS A
JOIN
    PRODLEVEL P ON A.Product_level =
P.Code_level
WHERE
    P.Group_level = 'RQ'
GROUP BY
    P.Division_level;
```

```
(Q3)
SELECT
    A.Retailer_level,
    AVG(A.UnitsSold) AS AverageUnitsSold
FROM
    ACTVARS A
JOIN
    PRODLEVEL P ON A.Product_level =
P.Code_level
JOIN
    Custlevel C ON A.Customer_level =
C.Store_level
WHERE
    P.Division_level = 'UV'
GROUP BY
    A.Retailer_level;
```

```
(Q4)
SELECT
    A.Product_level,
    AVG(A.UnitsSold) AS AverageUnitsSold
FROM
    ACTVARS A
JOIN
    TIMELEVEL T ON A.Time_level = T.Tid
WHERE
    T.Year_level = '2025'
GROUP BY
    A.Product_level;
```

```
(Q5)
SELECT
    P.Division_level,
    AVG(A.UnitsSold) AS AverageUnitsSold
FROM
    ACTVARS A
JOIN
    TIMELEVEL T ON A.Time_level = T.Tid
JOIN
    PRODLEVEL P ON A.Product_level =
P.Code_level
WHERE
    T.Month_level = '7'
GROUP BY
    P.Division_level;
```

3) We have created the extraction context after generating the Data Warehouse. It is a "query-attribute" matrix where each row designates a query of the load. The columns define the candidate attributes for the indexing procedure. The existence of an indexable attribute in a query is symbolized by 1 and its absence by 0 [To each query Qi and each attribute Aj, we associate a usage value of the attribute which is equal to 1 if the query uses the attribute Aj, 0 otherwise]. We illustrate the construction of this matrix through the following example. The "query-attribute" matrix obtained after the syntactic analysis of the load is composed of eleven columns and five rows (Table 9).

Table 9 : Query-attribute matrix

Tables	**PRODLEVEL**			**TIMELEVEL**			
Queries/Attributes	***Code_level***	***Group_level***	***Division_level***	***Tid***	***Year_level***	***Quarter_level***	***Month_level***
Q1	0	0	0	1	0	1	0
Q2	1	1	0	0	0	0	0
Q3	1	0	1	0	0	0	0
Q4	0	0	0	1	1	0	0
Q5	1	0	0	1	0	0	1

Tables	**CUSTLEVEL**	**ACTVARS**		
Queries/Attributes	***Store_level***	***Customer_level***	***Product_level***	***Time_level***
Q1	0	0	0	1
Q2	0	0	1	0
Q3	1	1	1	0
Q4	0	0	0	1
Q5	0	0	1	1

The "query-attribute" matrix obtained after parsing the payload is composed of 11 columns and 5 rows (Figure 5). It is subdivided according to the tables used in the payload for reasons of clarity and readability. This matrix is used by the CFPGrowth++ algorithm.

We applied our implementation of the CFPGrowth++ algorithm to the extraction context in order to select the most used candidate attributes in the system history that represent interesting candidates for the indexing operation.

4) We proceeded in the last step to the execution of the load of the queries on the generated Data Warehouse according to two scenarios (1) without creation of the indexes, (2) after creation of the indexes generated by the CFPGrowth++ algorithm.

During the execution of the load of queries on the Data Warehouse generated without creating indexes we calculated the execution time of each query of the load, After that we proceeded to calculate the execution time of each query of the load after creation of the indexes generated by the CFPGrowth++ algorithm. Figure 4 shows the times taken for the execution of the quests after the creation of the generated binary join indexes.

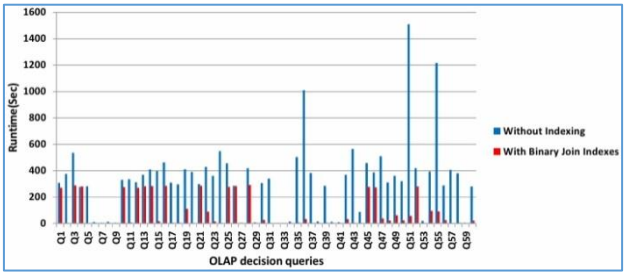


Figure 4 : Query execution time without creating indexes and after creating generated binary join indexes.

Our approach with generating candidate indexes by the CFPGrowth++ algorithm provides excellent performance improvements compared to running the query load without indexing.

Through our experimental study, we notice that the execution time is significantly improved after creating the binary join indexes. The Figure 5 illustrates the overall execution time saving for the entire load of OLAP decisional queries considered.

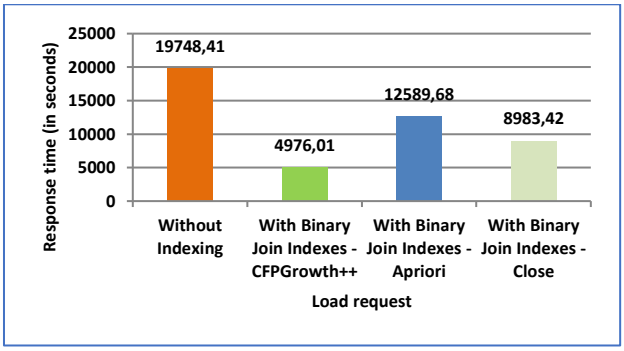


Figure 5 : Overall execution time of the load without creating indexes and after creating the generated binary join indexes.

As shown in Figure 5, the response time for decision-support query workloads without indexing was 19748.41 seconds, while the use of Binary Join Indexes generated with CFPGrowth++ reduced this to 4976.01 seconds, achieving a performance gain of approximately 75%. In contrast:

Apriori-based indexing reduced response time to 12589.68 seconds

Close-based indexing reduced it to 8983.42 seconds

This confirms that CFPGrowth++ outperforms these alternative frequent itemset mining algorithms in index selection efficiency for OLAP workloads.

The results obtained confirm the great usefulness of binary join indexes for the optimization of OLAP decisional queries. The execution time of these queries is significantly lower with the use of binary join indexes.

The experiments carried out show that the index configuration generated by the proposed approach allows a significant performance gain of around 75%.

To evaluate the effectiveness and robustness of the proposed approach for frequent pattern-based binary join index selection in OLAP query optimization, a series of 11 independent performance tests were conducted on varying OLAP query workloads. The experimental results demonstrated consistent performance improvements ranging from **74.20% to 75.96%**.

The statistical analysis confirmed the reliability of these performance gains. The mean improvement across all tests was **74.58%**, with a standard deviation of **0.50**, indicating low variability in the observed results. A one-sample t-test was performed to determine whether the observed improvements were statistically significant compared to a baseline of no performance gain. The test yielded a **t-statistic of 493.72** and a corresponding **p-value of** 2.86×10^{-23}, which is well below the conventional significance threshold of 0.001. This confirms that the observed improvements are statistically significant at a **95% confidence level**.

Moreover, a 95% confidence interval for the mean performance improvement was calculated as **[74.24%, 74.92%]**, further supporting the consistency and robustness of the proposed method's effectiveness under different query scenarios. These results clearly validate the practical benefits and generalizability of the

CFPGrowth++-based approach in optimizing complex OLAP workloads.

6 Discussion

This study is situated within the context of selecting optimal indexes to enhance the performance of decision-making queries, particularly in OLAP environments. Several approaches have been proposed previously, notably those by Aouiche et al. [27], who employed closed frequent pattern mining using the Close algorithm to prune the search space, primarily based on attribute usage frequency. However, this method can lead to the elimination of potentially relevant indexes, especially for attributes belonging to large dimension tables, where usage frequency alone does not guarantee effective optimization.

On the other hand, Bellatreche et al. [28][29][32] emphasized that access frequency alone is not a sufficient criterion for effective index selection. Their approach incorporates additional parameters, such as table sizes and page characteristics, to better balance the relevance of indexes. Nevertheless, this increased complexity can result in higher computational costs during pattern generation.

Our approach, utilizing the CFPGrowth++ algorithm, offers a significant advancement over these methods. Indeed, CFPGrowth++ enables faster and more scalable extraction of frequent patterns. Its ability to handle multiple support thresholds allows for a more refined exploration of itemsets, which contributes to better adaptation to large data volumes and performance requirements.

Regarding performance, the improvements offered by CFPGrowth++ can be attributed to its optimized structure, which reduces processing time and memory consumption compared to traditional algorithms like Apriori or Close. It also better manages the trade-offs between computational cost and effectiveness. However, this increased efficiency may come with some storage overhead, especially if a large number of frequent patterns are generated, necessitating careful management to avoid memory overload.

In our proposed approach, CFPGrowth++ was chosen for its efficiency in mining frequent patterns through a compact tree-based structure and its flexibility in handling multiple support thresholds. However, we recognize that as the number of attributes and queries increases in real-world data warehouses, the size of the pattern base and the computational overhead can grow significantly.

To manage this, several strategies can be applied, such as:

Adjusting support thresholds dynamically to limit the number of frequent itemsets generated in dense workloads.

The evaluation with applying a constraint on the total storage space consumed by the generated indexes.

Partitioning the workload or focusing on query subsets that target the most resource-intensive operations.

Parallelizing the mining process across distributed computing environments to improve processing times and scalability.

CFPGrowth++ stands out for its speed, scalability, and accuracy, making it a promising solution for index selection in contexts where efficient management of large data volumes is critical. It represents a notable improvement over previous techniques, while also requiring attention to potential storage and computational costs.

7 Conclusion

Within the realm of Data Warehouses schematized in a star relational model carried out via OLAP decision-making queries, very high response time remain more than ever a crucial issue.The goal of this work is to improve the Data Warehouse performance.The proposed approach for optimizing system performance by minimizing response time is based on finding frequent patterns for automatic selection of binary join indexes in relational Data Warehouses modeled by a star schema through generation of a configuration of binary join indexes based on the implementation of the CFPGrowth++ algorithm.The results show the particular performance of the binary join indexes recommended by the CFPGrowth++ algorithm implemented for relational Data Warehouses. Our study demonstrates that applying data mining techniques for the automatic selection of binary join indexes in relational Data Warehouses is a promising strategy, offering encouraging results and opening up several opportunities for future research and optimization. Other possible improvement is to consider multiple parameters to generate the final index configuration. In future work it important to consider in particular of the selectivity factors and the cardinalities of the attributes or the sizes of the dimension tables.

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https://doi.org/10.31449/inf.v49i27.11195 Informatica **49** (2025) 379–394 **379**

Semi-Automatic Construction and Benchmarking of a Word-Segmented Corpus for Lao Using LLMs and Transformer Models

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Keywords: Word segmentation, low-resource languages, corpus construction, semi-automatic method, Lao language, NLP

Word segmentation is a fundamental task in Natural Language Processing (NLP), particularly for continuous-script languages such as Lao and Thai, where the absence of spaces between words makes boundary detection highly challenging. In this paper, we present the first publicly released Lao word-segmentation corpus together with a semi-automatic construction pipeline that combines automatic pre-annotation and human verification. Specifically, pre-annotation was generated primarily with GPT-4o (May 2024 snapshot), while a smaller subset was produced using GPT-5o, and all outputs were subsequently corrected through systematic verification by trained native annotators. A senior Lao linguist served as adjudicator to resolve difficult cases and enforce consistency. The final resource comprises 10,000 training sentences and a 1,000-sentence gold-standard test set. To demonstrate utility, we benchmarked Lao word segmentation with an XLM-RoBERTa transformer model, achieving a boundary-level F1 score of 0.75, which surpasses the widely used LaoNLP baseline (0.71). This corpus fills a critical resource gap for Lao and provides a reproducible foundation for future research on word segmentation, POS tagging, machine translation, and other downstream tasks in low-resource language processing.

Povzetek: Članek predstavi prvi javni korpus za laoško segmentacijo besed, zgrajen polavtomatsko, z 10k/1k delitvijo in Transformerji ter demonstrira uporabnost z osnovnim poskusom, kar odpira pot za nadaljnje raziskave.

1 Introduction

Word segmentation is a fundamental task in Natural Language Processing (NLP), especially for continuous-script languages such as Lao and Thai, where words are not separated by spaces or delimiters [21, 22]. This characteristic makes the identification of word boundaries particularly challenging. Accurate segmentation serves as the basis for downstream tasks including machine translation, information retrieval, text summarization, and sentiment analysis [23]. However, the lack of publicly available annotated corpora has severely limited research on Lao NLP [14].

Traditional approaches to word segmentation rule-based or dictionary-based have shown limited success [9, 17]. While rule-based systems provide transparency and flexibility for new words, they require extensive manual effort to create and maintain consistent rules. Dictionary-based approaches can recognize known words effectively but fail with compound terms, dialectal variations, or newly coined words [18]. More recently, machine learning and deep learning methods have demonstrated strong performance in high-resource languages [3, 2], but their heavy reliance on large annotated corpora renders them unsuitable for low-resource settings such as Lao [19, 12].

Although there has been progress in semi-supervised and cross-lingual transfer methods for other low-resource languages [5, 4, 6], there remains a critical gap: Lao still lacks an openly available, high-quality word-segmented corpus. Without such resources, it is difficult for researchers to build, compare, and advance models for Lao NLP [14]. In practice, the absence of a standardized, publicly available corpus means that most prior studies relied on small, privately collected datasets, which vary in domain, size, and annotation quality. This fragmentation prevents fair comparison between models and makes it difficult to reproduce results across research groups. Furthermore, modern neural approaches such as transformer-based models require sufficiently large and consistent annotated data to achieve stable performance; without such data, progress on Lao NLP has remained limited and scattered.

In this paper, we address this gap by introducing the first publicly released word-segmented corpus for Lao. Our corpus was constructed using a semi-automatic method: large language models (LLMs) generated initial annotations, which were then systematically reviewed and corrected by native Lao annotators following annotation guidelines. This approach balances efficiency with quality assurance, enabling the creation of a linguistically consistent dataset at reduced cost. Our contributions are:

1. Proposing a semi-automatic method for constructing

high-quality annotated corpora in low-resource languages, combining large language models for initial annotation with systematic verification by native annotators.

2. Building and releasing the first publicly available corpus of word-segmented Lao sentences, consisting of 10,000 sentences and a gold-standard test set of 1,000 sentences.

3. Benchmarking the dataset with a transformer-based word segmentation model (XLM-R), which achieves state-of-the-art performance on Lao word segmentation, outperforming existing Lao tools by a substantial margin (see Table 5).

Guided by these goals, we pose three research questions to structure the empirical study:

(i) Can LLM-assisted pre-annotation with expert native verification produce a high-quality Lao word-segmentation corpus?

(ii) How does performance scale with corpus size under native-verified supervision?

(iii) To what extent does the resulting corpus improve model generalization relative to existing Lao segmenters?

We answer these in Secs. 3.2–3.4 (pipeline and quality controls), Table 4 (learning curve), and Table 5/Sec. 6.4 (comparisons and analysis).

Our corpus and baseline models are publicly available at `https://github.com/HaHVU/HVULao_NLP`, offering a valuable resource for advancing Lao NLP and supporting future work on other low-resource languages.

2 Related works

Word segmentation and POS tagging in low-resource languages, especially continuous-script languages such as Lao and Thai, remain a challenging task due to limited data and linguistic complexity [21, 22, 14, 24]. Traditional approaches such as rule-based or dictionary-based systems struggle with new words, compound terms, and ambiguous contexts, making them ineffective when used alone [17, 19]. To overcome these limitations, recent research has explored cross-lingual transfer, data augmentation, and semi-automatic methods [2, 5, 11, 12, 13, 6, 8].

Cross-lingual transfer methods have shown promise by leveraging resources from high-resource languages. Conneau et al. [2] introduced XLM-R, a large multilingual model trained on more than 100 languages, which facilitates transfer learning for low-resource languages such as Lao. Similarly, Eskander et al. [5] proposed an unsupervised projection method using parallel corpora (e.g., the Bible) to transfer POS information across languages, demonstrating its potential in extremely low-resource scenarios.

Data augmentation techniques have also been proposed to compensate for the lack of annotated corpora. Shen et al. [12] worked on ancient Chinese, another low-resource continuous-script language, and showed that hybrid tagging schemes and synthetic data generation could significantly enhance both segmentation and tagging accuracy. Plank et al. [13] demonstrated that fine-tuning pre-trained models such as BERT or RoBERTa on small annotated datasets can yield strong results, reducing the need for large-scale resources.

Another research line focuses on semi-automatic or weakly supervised annotation. Sanjeev Kumar et al. [8] further introduced a parallel POS-tagging dataset for Angika, Magahi, Bhojpuri, and Hindi, highlighting the importance of making annotated corpora publicly available for community use. *Comparable challenges and solutions have also been reported for other continuous-script languages in the region such as Khmer, Burmese, and Tibetan.*

For Khmer, recent work has released a 20,000-sentence corpus with manual tokenization and POS tags and established benchmarks from CRF to LSTM–CRF [25]; joint segmentation+POS models based on BiLSTM have also been explored [31]. For Myanmar (Burmese), early segmentation relied on maximum matching and CRF [26, 27], and more recent studies propose joint models (syllable/word segmentation and POS) leveraging BERT [28]. For Tibetan, classical approaches used word-position tagging with CRF [30], while recent neural models perform joint segmentation and POS with BiLSTM/IDCNN/CRF architectures [29, 30]. Taken together, these lines of work highlight a common trend: segmentation-first or joint modeling is necessary in languages with minimal orthographic cues, providing a relevant backdrop for our Lao study.

While the above discussion outlines major methodological directions, Table 1 provides a concise comparison across representative studies, summarizing their language scope, methodological type, dataset availability, and performance. This overview highlights the persistent lack of publicly available Lao resources and justifies our focus on constructing a fully open, native-verified corpus.

Beyond word segmentation and POS tagging, several recent studies have also emphasized the importance of constructing reliable corpora and domain-specific resources for advancing NLP. For example, Hu et al. [32] developed a clinical corpus for characterizing pituitary adenomas and demonstrated its application in large language models. Ahmad et al. [33] designed and evaluated a hate speech detection corpus for Arabic. Shao et al. [34] proposed an integrated NLP method for text mining and visualization of underground engineering reports. Although focusing on different application domains, these works share with our study the same objective of building high-quality linguistic resources that enable modern NLP research.

Table 1: Related work on segmentation/POS for low-resource continuous-script languages: methodology, key method/model, dataset availability, benefits, and drawbacks.

Ref.	Language(s)	Methodology / Key method	Dataset availability	Benefits	Drawbacks
[21, 22]	Thai	Data-driven word segmentation	Not public (task-specific)	data-based learning	Domain dependence; limited generalization
[14]	Lao	Dictionary-based segmentation	Open dictionaries; Y-Cup-2020 corpus	Open-source toolkit	no deep learning or contextual modeling
[25, 31]	Khmer	BiLSTM (char) joint seg + POS	Khmer POS (12k)	Unified; 97.1% seg. acc.; simple	Small dataset; no emb.; mono Khmer
[12, 32, 34]	Chinese	Hybrid tagging + *data augmentation*/CCNLP platform/ BERT + BiLSTM + CRF	not public	Boosts seg/POS with synthetic data	Dependent on pseudo-data quality; domain shift
[26, 27, 28]	Burmese	CRF–SVM–LM compare; CRF boundary; BERT joint tagger	non-public	joint reduces errors; 1st neural Burmese WSG–POS	Limited domain; inconsistent annotation
[30, 29]	Tibetan	BiLSTM+IDCNN+CRF joint; 6-tag CRF + post-processing	non-public	OOV-robust; effective joint model	Feature-based; needs larger corpus
[17, 19]	Slovene/ Vietnamese	lexicon-based/Hybrid	available for research	handles overlap ambiguities effectively	depends on lexicon completeness
[8]	Angika, Magahi, Bhojpuri, Hindi	Min.-supervised morph. seg. (Morfessor / AG / CRF)	4-lang wordlists; annotated/unannotated	Comparative; error-analytical; low-resource guidance	No novel model; 4-lang scope only
[3]	English, Estonian, Finnish, Turkish	MuRIL-Hi + Look-back	708-sent. UD-parallel, public	Token fix; strong zero-shot	Small / domain-limited; relies on Hindi transfer
[2]	100+ (incl. Lao)	Transfer learning with **XLM-R**	Code/models, CC-100 data	SOTA on XNLI/MLQA/NER	extremely compute-intensive
[5]	12 target + 6 source	annotation projection + BiLSTM	Parallel corpora	Unsupervised; robust multi-source transfer	Domain bias; limited lexical/morph coverage
[11]	104 languages	mBERT transfer (fine-tuning)	Models public; Wikipedia (104 langs)	Good POS transfer with small labels	Inconsistent for continuous scripts; needs gold data
[13]	22 languages	BiLSTM + W-C Emb + LOGFREQ Loss	v1.2, WSJ public	OOV-robust; low-data generalization	Label-noise sensitive; unstable on small datasets
[6]	17 low-resource + 15 high-resource	GLP = GNN Label Propagation + Self-Learning	Parallel Bible, UD v2.10 public	Unsupervised POS transfer; works for unseen langs	High compute; Bible-domain bias
[15]	101 languages	Subword tokenizer (SentencePiece/BPE) as heuristic segmentation	Corpora public (Flores)	Easy to apply cross-lingually	Heuristic splits; not true Lao word boundaries
This work	**Lao**	**LLM-assisted pre-annotation + native adjudication; XLM-R fine-tuned**	**Fully released (10k train + 1k gold test)**	**High-quality, reproducible Lao corpus; SOTA Lao segmentation**	**Current domains: news/official; social/dialogue future work**

Despite these advances, Lao still lacks an openly available, high-quality corpus for word segmentation [14, 15]. Most existing studies rely on transfer or augmentation but do not address the fundamental bottleneck of corpus construction. Our work differs from prior approaches by proposing a semi-automatic method that not only leverages large language models for initial annotation, but also ensures linguistic quality through systematic verification by native Lao annotators. This combination enables us to build and release the first public word-segmented corpus for Lao, filling a critical resource gap and providing a reproducible foundation for future low-resource NLP research.

3 Our proposed method

Our goal is to efficiently construct a high-quality, publicly released word-segmented corpus for Lao using a semi-automatic pipeline that combines large language models (LLMs) with systematic human verification. The pipeline is illustrated in Figure 1 and consists of three main stages:

1. **Pre-annotation with LLMs (No1 → No2).** Raw Lao sentences collected from reliable sources are first pre-annotated by an LLM (e.g., GPT-5o) to produce raw word-segmented candidates.

2. **Expert verification by native annotators (No2 → No3).** Native Lao annotators review and correct the pre-annotations following written guidelines, resolving boundary ambiguities, compound words, and edge cases. The verified outputs are consolidated into the high-quality word-segmented corpus.

3. **Model bootstrapping.** The verified corpus (No3) is then used to fine-tune a transformer-based word-segmentation model, reducing future reliance on LLMs and lowering annotation cost.

This design explicitly balances efficiency and quality: LLMs drastically reduce manual effort, while linguist verification ensures internal consistency and prevents systematic LLM errors from propagating.

3.1 Collecting Lao monolingual sentences

The first stage of our semi-automatic pipeline involves the collection of naturally occurring Lao sentences to construct a representative monolingual corpus for word segmentation. To ensure linguistic reliability and coverage, we deliberately targeted trustworthy sources that follow grammatical conventions and provide domain diversity. Specifically, we gathered texts from official government websites, national news portals, academic institutions, and legal repositories. These domains cover a broad range of topics including politics, education, law, culture, and daily news thereby contributing to both lexical richness and structural variety, which are essential for developing robust NLP resources.

All collected texts underwent a standardized pre-processing procedure. This included removing duplicated sentences, discarding incomplete or noisy fragments, and normalizing formatting inconsistencies such as irregular punctuation or encoding artifacts. Through this filtering process, we ensured that only linguistically sound and representative sentences were retained for subsequent processing.

As a result, we compiled a sufficiently large dataset to support both training and evaluation. Specifically, we constructed a gold-standard test set of 1,000 sentences for reliable benchmarking, and a high-quality training corpus of 10,000 sentences for model development. Table 2 summarizes the primary sources from which the monolingual Lao data were collected.

3.2 LLM-based pre-annotation

In this stage, we leverage a large language model to generate initial word-segmentation candidates for Lao sentences. The model is instructed to output only segmented text in a strict, machine-checkable format, without any additional linguistic annotations. This design minimizes ambiguity in the output and simplifies subsequent verification by human annotators.

To increase the robustness of LLM-generated segmentations in a low-resource setting, we adopt the following strategies:

– **Task-specific prompting.** The prompt provides explicit instructions to segment Lao sentences into word tokens, along with format requirements that enforce one token per unit separated by spaces or line breaks.

– **Few-shot demonstrations.** The prompt includes short Lao examples that illustrate typical segmentation challenges, such as reduplications, clitics, compound words, and punctuation, thereby guiding the model toward consistent boundary decisions.

– **Error-driven refinement.** Prompts are iteratively refined based on systematic error analyses during pilot experiments. Frequent issues, such as over-segmentation of function words or under-segmentation around punctuation, are explicitly highlighted and corrected through improved instructions and examples.

For reproducibility, each pre-annotated sentence is stored together with its original unsegmented form. This ensures provenance tracking and allows researchers to replicate or refine the pre-annotation process in future studies.

In practice, the majority of pre-annotations were generated with GPT-4o (OpenAI, API snapshot May 2024). A small portion of pilot data was also produced using

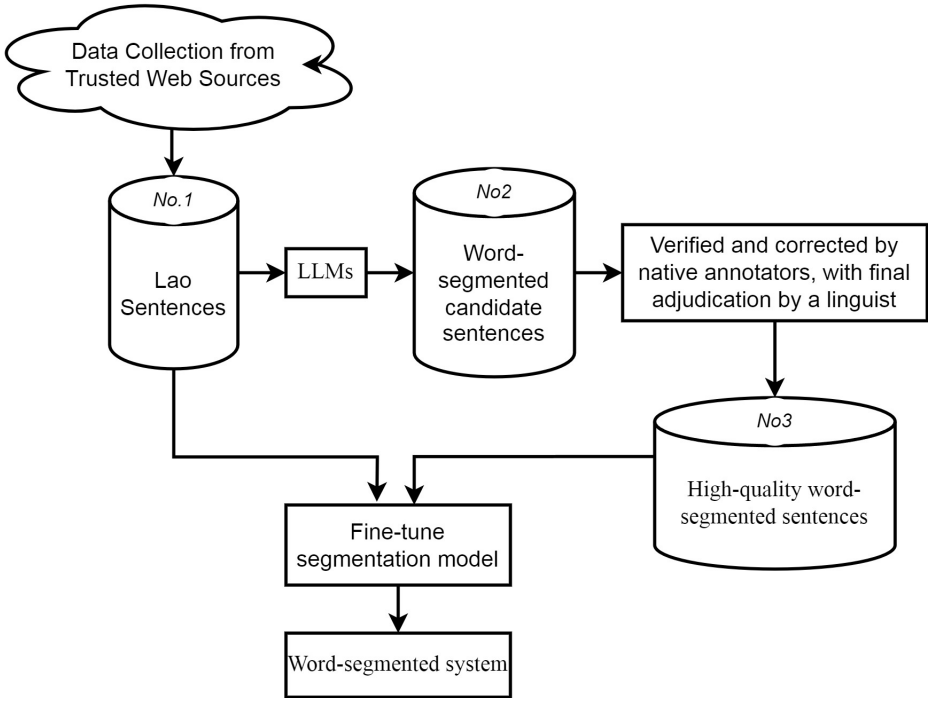


Figure 1: Semi-automatic pipeline for constructing the Lao word-segmented corpus

Table 2: Domain sources and sentence distribution in the Lao monolingual corpus

No.	Source / Domain	Sentences	Proportion (%)
1	National Assembly of Laos (na.gov.la)	1,240	12.4
2	Lao News Agency – KPL (kpl.gov.la)	2,130	21.3
3	Ministry of Education and Sports (moes.edu.la)	920	9.2
4	Lao Official Gazette (laogov.la)	870	8.7
5	National University of Laos (nuol.edu.la)	960	9.6
6	Vientiane Times (vientianetimes.org.la)	1,980	19.8
7	VOV Lao (vovworld.vn/lo-LA.vov)	1,900	19.0
Total	**7 trusted sources**	**10,000**	**100.0**

the subsequently released GPT-5o, demonstrating that the pipeline is model-agnostic and can flexibly adopt future LLMs.

We configured GPT-4o and GPT-5o with the following decoding parameters: *temperature = 1.0, top_p = 1.0, max_tokens = 512, frequency_penalty = 0, presence_penalty = 0, stop = none*. This fixed configuration, together with the strict prompt design, ensured stable and format-consistent outputs.

For reproducibility, we documented the model identifier, snapshot date, and prompt version used in the pre-annotation process.

An excerpt of the instruction prompt is presented below:

You are a Lao word segmentation assistant.
TASK: Insert spaces between Lao word tokens.
RULES:
1) Output only the segmented sentence.
2) One token per unit, separated by spaces.
3) Punctuation marks and particles are separate tokens.

Input:
ท่านฟ้ามบินมีนเน้นໜັกว่าแหล่งทึนของทะนาคานพัดทะนาอาซีได้นำใช้ย่างมีปะสิดทิผัน,

Output:
ท่าน ฟ้ามบินมีน เน้นໜັก ว่า แหล่งทึน ของ ทะนาคาน พัดทะนา อาซี ได้ นำใช้ ย่าง มี ปะสิดทิผัน ,

(Mr. Pham Binh Minh emphasized that the Asian Development Bank's funds have been used effectively.)

After generating automatic pre-annotations as candidate segmentations, the next step involves manual verification to ensure linguistic accuracy and consistency.

3.3 Verification by native annotators

All candidate segmentations produced by the LLM are systematically verified by trained native Lao annotators through a custom web-based interface. This interface visualizes differences between the LLM output and the corrected version, allowing annotators to focus on token boundary modifications rather than re-annotating entire sentences.

Annotators strictly follow a written segmentation guideline that was developed to ensure consistency and reproducibility across annotators. The guideline specifies detailed treatments for common and challenging cases, including:

- Handling of compound words, multi-word expressions, numerals, dates, and named entities;
- Disambiguation heuristics for function words, particles, and ambiguous morphemes;
- Normalization rules for punctuation and mixed-script tokens (e.g., Latin characters or digits).

To balance efficiency and quality, edits are intentionally minimal and surgical: annotators correct only where necessary (fix-only), thereby maintaining annotation throughput while ensuring internal consistency. When disagreements arise, cases are escalated to a native linguist, who adjudicates and finalizes the decision.

Annotators underwent a short training phase on a pilot set with iterative feedback from the senior linguist to ensure consistent application of the guidelines. To assess annotation consistency, we randomly selected 5% (500 sentences) for double annotation. The inter-annotator segmentation F1 was 0.80, indicating substantial agreement and reliable boundary consistency.

In practice, the annotation team consisted of four trained native annotators and one native linguist, working over a period of eight months to complete the verification process. This sustained effort highlights both the difficulty of Lao word segmentation and the scale of our contribution. In particular, the 1,000-sentence test set was carefully constructed and validated by the native linguist to ensure its reliability as a gold-standard benchmark, providing a trusted basis for evaluating segmentation models and supporting reproducible research.

3.4 Joint pre-annotation and adjudication (segmentation + POS)

For efficiency, we obtain a *joint* LLM pre-annotation that includes both word boundaries and POS labels. Trained native annotators then correct segmentation and POS in a single pass using a diff-based interface; disagreements are adjudicated by a native linguist. The released dataset therefore contains (i) a gold word-segmentation layer and (ii) an aligned gold POS layer. To keep the scope focused, this paper evaluates models only for word segmentation, while the POS layer is released as an additional resource and its evaluation is left for future work.

4 Corpus statistics and analysis

To assess the coverage and linguistic diversity of our resource, we performed a systematic analysis of both the training corpus (10,000 sentences) and the gold-standard test set (1,000 sentences). The statistics are summarized in Table 3.

The corpus exhibits solid lexical coverage, with 13,339 unique word types in the 10k training set and 2,901 in the 1k test set. The average sentence length is 19.37 tokens in training and 15.73 tokens in test, which is consistent with written Lao drawn from news, academic, and legal sources. Importantly, **80.1%** of the word types in the test set also appear in the training vocabulary, indicating substantial lexical overlap and making the resource suitable for benchmarking segmentation models.

Figure 2 reports the sentence length distribution for the 10k training corpus. The distribution is right-skewed with a clear mode at 10–14 tokens. The bulk of sentences lie between 10 and 29 tokens, a smaller but noticeable portion are short (under 10 tokens), and long sentences become progressively rarer; only a small tail contains 40+ tokens. This shape reflects the structural variety of Lao, from short declaratives to longer multi-clause sentences, and its implications for corpus utility are worth noting.

In particular, the majority of sentences are of medium length, which provides abundant context for learning boundary patterns. The concentration around 10–29 tokens suggests that the corpus predominantly captures expository and declarative structures, typical of news and formal prose. By contrast, the sparsity of very long sentences indicates that highly nested or multi-clause constructions are under-represented, which may limit generalization in those cases. Thus, while the training set is well-suited for developing segmentation models in standard written contexts, future extensions could benefit from incorporating more long-form texts to cover complex syntactic patterns.

Complementing the training set, the gold-standard test set exhibits a similar right-skewed profile with a mode at 10 - 14 tokens and an average of 15.73 tokens per sentence. Most sentences fall between 5 and 29 tokens ($\approx$ **94.1**%), with the majority concentrated in 10–29 tokens ($\approx$**77.6**%), short sentences under 10 tokens account for $\approx$ **17.3**%, sentences of 30–39 tokens make up $\approx$ **4.3**%, and very long sentences ($\geq$ 40 tokens) are rare ($\approx$ **0.5**%). This mirrors the structural variety observed in Lao prose while keeping a long but light tail of complex sentences (see Figure 3), and its distribution offers further insights into evaluation conditions.

Like the training set, the majority of test sentences are of medium length, which provides abundant context for assessing segmentation accuracy in standard prose. The

Table 3: Statistics of the Lao word-segmented corpus

Statistic	Training Corpus (10k)	Test Set (1k)
Number of sentences	10,000	1,000
Total tokens	193,714	15,730
Mean sentence length	19.37	15.73
Average characters per token	4.32	4.26
Unique word types	13,339	2,901
Vocabulary coverage (test vs. train)	80.1%	

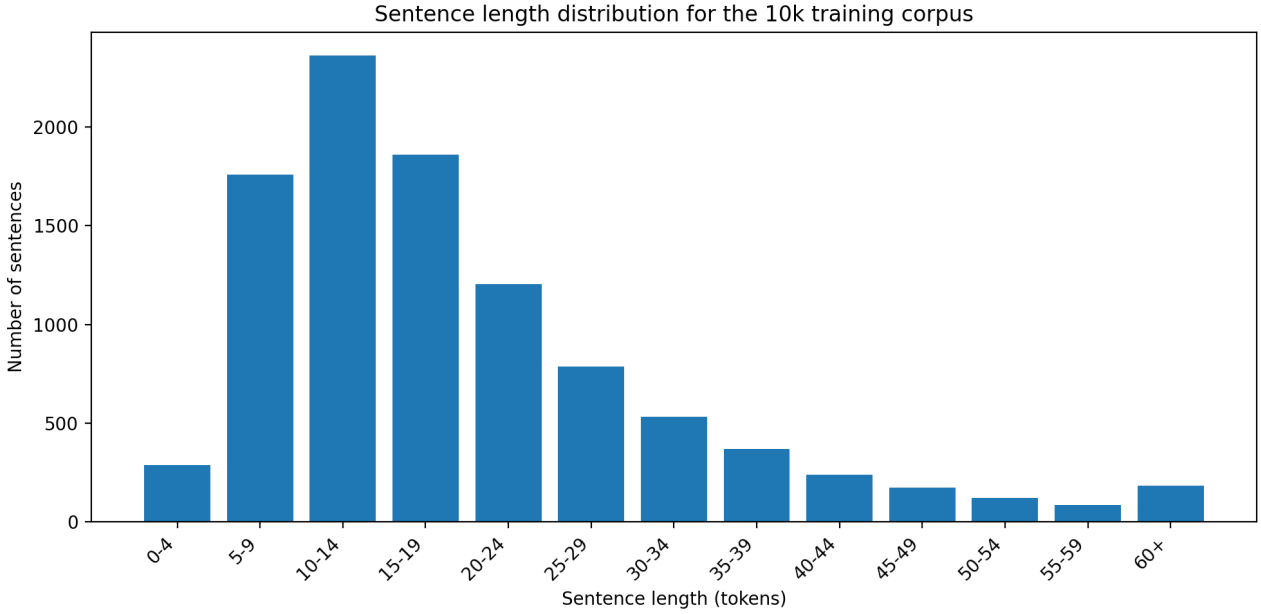


Figure 2: Sentence length distribution (in tokens) for the 10k training corpus

noticeable share of short sentences ensures coverage of cases dominated by function words and particles, while the scarcity of very long sentences means that robustness on deeply nested structures should be interpreted with caution. Overall, the test distribution closely aligns with the training profile, which minimizes domain shift and supports reliable benchmarking, but also highlights the need for future expansions with more conversational and complex sentence types.

5 Corpus linguistic characteristics

A qualitative inspection of the corpus highlights several key linguistic features:

- Compound words and reduplication: Lao frequently forms compound nouns and uses reduplication for emphasis or plurality, both of which challenge segmentation.
- Function words and particles: Common particles (e.g., negation, aspect markers, discourse particles) are often short and can be easily under-segmented.
- Named entities and numerals: Mixed-script tokens (Lao with Latin characters or digits) appear frequently in news and official texts, requiring consistent annotation.
- Ambiguity in boundaries: Certain morphemes serve multiple syntactic functions depending on context, demanding careful disambiguation during annotation.

These characteristics underline the importance of having a carefully validated gold-standard test set. As described in Section 4, the 1,000-sentence test set was meticulously constructed and adjudicated by a native linguist, ensuring high reliability and reproducibility for future benchmarking.

Overall, the corpus provides not only scale but also linguistic variety, making it a valuable resource for training robust segmentation models and studying Lao as a low-resource continuous-script language.

POS layer: Beyond boundaries, the corpus includes a gold POS layer vetted by native annotators and aligned to the released tokenization. We provide the tagset, labeling rules, and examples of difficult cases to ensure consistent downstream use; POS modeling is left to future work.

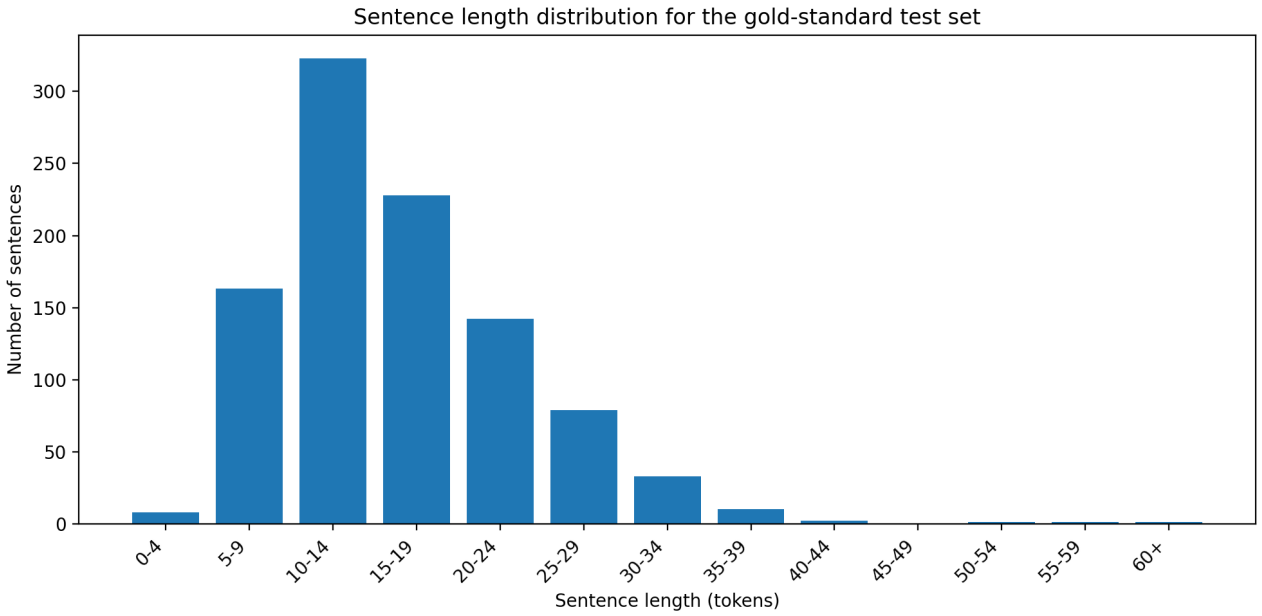


Figure 3: Sentence length distribution (in tokens) for the gold-standard test set

6 Experiments

6.1 Task, data splits, and metrics

Our goal is to verify that the proposed corpus enables accurate *Lao word segmentation*. We treat segmentation as token classification with a **BIO** scheme over subword tokens. Given the tokenizer's offset mapping, we label the first subword of a word as `B-WORD`, subsequent subwords as `I-WORD`, and non-text/padding as `O`; gold boundaries are recovered from the labels.

We use the **10k** verified sentences for training/validation with a **15%** random validation split (seed $=$ 42). The **1k** native-validated set is held out strictly for final testing. Evaluation is conducted at the *boundary level*: a predicted boundary is correct *iff* it matches a gold word boundary. We report **Precision**, **Recall**, and **F1**.

6.2 Model and training setup

We fine-tune **XLM-RoBERTa-base** [2] using the Hugging Face transformers stack. Training uses **AdamW** with learning rate 2×10^{-5}, weight decay 0.02, sequence length 128, batch size 4 per device with **gradient accumulation** $= 4$, and **10** epochs. We enable `fp16` mixed precision and a warmup ratio of **0.1**. Models are evaluated every epoch and the best checkpoint is selected by validation loss with **early stopping** (patience $= 5$, at most two checkpoints retained).

Computing environment All experiments were conducted on a dedicated server running Ubuntu 20.04.6 LTS (Focal Fossa), equipped with an NVIDIA GeForce RTX 3090 GPU (24 GB VRAM). The implementation used PyTorch and Hugging Face Transformers, following the setup described above (XLM-RoBERTa-base backbone, sequence length 128, batch size 4 per device with gradient accumulation 4, AdamW with learning rate 2×10^{-5}, weight decay 0.02, warmup ratio 0.1, 10 epochs, fp16 enabled, evaluation/saving each epoch, and early stopping with patience 5). On this setup, each training run required about 40 minutes.

6.3 Learning curve

To examine data efficiency, we fine-tune with {2k, 4k, 6k, 8k, 10k} training sentences while keeping the test set fixed. Results on the 1k gold test set are shown in Table 4.

Table 4: Learning-curve results on the 1k gold test set (boundary-level). Values are **mean** $\pm$ **SD** over five random seeds (13, 21, 42, 87, 123).

Training Data	Precision	Recall	F1 score
2,000	0.64 ± 0.01	0.46 ± 0.02	0.53 ± 0.01
4,000	0.73 ± 0.02	0.64 ± 0.01	0.68 ± 0.01
6,000	0.69 ± 0.01	0.75 ± 0.01	0.72 ± 0.01
8,000	0.70 ± 0.01	0.75 ± 0.01	0.73 ± 0.01
10,000	0.76 ± 0.01	0.74 ± 0.01	$\mathbf{0.75} \pm 0.01$

Observations. (i) Performance increases steadily with more training data; gains start to taper after $6 - 8$k sentences, suggesting diminishing returns once the model has seen sufficient boundary patterns. (ii) Improvements at larger sizes indicate that *native-verified* consistency benefits generalization as much as scale.

To assess robustness, we fine-tuned five independent runs with different random seeds (13, 21, 42, 87, 123).

Table 4 reports the mean ± standard deviation (SD) of each metric. The extremely small SD values ($\leq$ 0.02) demonstrate that the model's learning behavior is stable and not sensitive to random initialization, confirming the statistical reliability of the observed trend.

6.4 Comparison with existing Lao segmenters

We compare our model against five baselines: a machine learning–based sequence labeling model (**CRF++**[1]), a widely used Lao segmenter (**LaoNLP**[2]), a subword-based tokenizer from the **Flores**-101 benchmark (**Flores**[3]), a multilingual transformer baseline (**mBERT**[4]), and a Thai Word Segmentation using SentencePiece model (**Thai-SP**[5]). Table 5 reports boundary-level scores on the same 1k gold test set. [14, 15, 3, 11, 7, 16].

Table 5: Comparison on the 1k gold test set (boundary-level)

Model	Precision	Recall	F1 Score
CRF++	0.15	0.04	0.06
LaoNLP	0.71	0.71	0.71
Flores	0.56	0.45	0.50
Thai-SP	0.34	0.10	0.15
mBERT	0.33	0.11	0.16
Our model	**0.76**	**0.74**	**0.75**

For completeness, both mBERT and Thai-SP were evaluated under the same boundary-level setting on the 1k gold test set. Their weak performance (mBERT: F1 = 0.16; Thai-SP: F1 = 0.15) indicates that neither multilingual transformers nor related-language tokenizers transfer effectively to Lao without in-language supervision.

The weak performance of CRF++ (F1 = 0.06) and mBERT (F1 = 0.16) further confirms the inherent difficulty of Lao segmentation and the necessity of a high-quality corpus. These baselines serve not merely as points of comparison but as evidence that our corpus effectively exposes the limits of existing methods, traditional statistical models lack contextual understanding, while generic multilingual transformers and cross-lingual tokenizers struggle with continuous scripts and low-resource settings. Our fine-tuned XLM-R model outperforms all baselines across every metric. Compared with CRF++ and mBERT, it achieves substantially higher precision and recall, confirming that contextualized representations capture boundary regularities that traditional statistical and generic multilingual models fail to learn. When evaluated against the off-the-shelf LaoNLP segmenter under its default configuration, XLM-R demonstrates a markedly better balance between precision and recall, effectively reducing both over-segmentation and under-segmentation. The weaker performances of Flores and Thai-SP further underscore the importance of language-specific supervision and in-language adaptation for Lao.

[1] https://taku910.github.io/crfpp/
[2] https://github.com/wannaphong/LaoNLP
[3] https://github.com/facebookresearch/flores
[4] https://huggingface.co/bert-base-multilingual-cased
[5] https://github.com/wannaphong/thai-word-segmentation-sentencepiece

7 Discussion

Our experiments address a central question: *does the proposed corpus enable accurate and reproducible Lao word segmentation?* The results support an affirmative answer and lead to several observations.

Data quality and coverage: The corpus balances scale and linguistic variety: the 10,000-sentence training set contains 13,339 word types and the 1,000-sentence test set contains 2,901 types, with 80.1% test types observed in training. Length profiles for train and test are similarly right-skewed (mode at 10–14 tokens), indicating that the held-out test is representative of the training distribution. Native-linguist adjudication enforces internal consistency, which is crucial for boundary-level supervision.

Effect of supervision volume: The learning curve in Table 4 shows steady gains as the number of supervised sentences grows from 2k to 10k, culminating in an F1 score of 0.75. Improvements taper after 6-8k sentences, suggesting diminishing returns once the model has encountered a sufficiently broad range of boundary patterns. This highlights that *label quality and consistency* are at least as important as raw quantity in low-resource settings.

Across five random seeds, the variance of Precision, Recall, and F1 was minimal (SD $\leq$ 0.02), indicating high experimental reproducibility. This confirms that performance differences across training-set sizes are statistically consistent rather than artifacts of random initialization.

Comparison to existing systems: On the same 1k gold test set and under boundary-level evaluation, our fine-tuned XLM-R model outperforms all baselines, including LaoNLP, Flores, Thai-SP, CRF++, and mBERT (Table 5). Gains are balanced in Precision and Recall, indicating fewer over-segmentations and fewer missed boundaries. In summary, contextualized representations trained on a native-verified corpus offer measurable advantages over simple subword-based segmentation heuristics (e.g., SentencePiece/BPE from the Flores pipeline) and over generic multilingual tokenizers.

Beyond absolute performance, the inclusion of CRF++, mBERT, and Thai-SP baselines provides a broader empirical context for assessing segmentation difficulty. The extremely low F1 of CRF++ (0.06) demonstrates that surface-level or feature-based models are unable to capture the morphosyntactic regularities of Lao, while mBERT (F1 = 0.16) and Thai-SP (F1 = 0.15, evaluated zero-shot on Lao) highlight that even large multilingual

Table 6: Breakdown of segmentation error types on the 1k gold test set. Percentages are measured over all boundary mismatches.

Error Type	Proportion	Typical Example
Over-segmentation	**7.0%**	*Reference:* บุนปีใหม่ลาว (‘Lao New Year’) *Predicted:* บุน ปี ใหม่ ลาว
Under-segmentation	**6.0%**	*Reference:* ທะນาคาม พัดทะนา อาຊี (‘Asian Development Bank’) *Predicted:* ทะนาคามพัดทะนาอาຊี
Total Error Rate	**13.0%**	

or related-language models fail to transfer effectively to a continuous-script, low-resource language. These observations reinforce that Lao presents a challenging test case for multilingual NLP, and that language-specific supervision remains indispensable despite recent advances in universal representation learning. Consequently, our corpus not only enables reproducible benchmarking but also establishes a clear baseline landscape for future research on more systematic transfer learning and cross-lingual adaptation.

Typical errors and quantitative analysis: A quantitative error breakdown was conducted on the 1k gold-standard test set to better characterize residual segmentation issues. Boundary mismatches were categorized into two main types: *over-segmentation* (spurious boundaries predicted inside a gold token) and *under-segmentation* (missing boundaries between adjacent gold tokens). Overall, the model achieved an **F1 score of 0.75**, with a small Precision–Recall gap (0.76 vs. 0.74) indicating a mild tendency toward predicting extra splits. Table 6 summarizes the proportion of each error type, showing that over-segmentation slightly dominates (7.0%) over under-segmentation (6.0%), yielding an overall boundary error rate of 13%.

Representative examples: Closer inspection of model outputs reveals systematic error patterns that reflect the morphosyntactic nature of Lao. In ทะนาคามพัดทะนาอาຊี (‘Asian Development Bank’), the model produced a single token instead of the correct segmentation ทะนาคาม พัดทะนา อาຊี, illustrating typical *under-segmentation* of multi-word named entities. Conversely, in บุนปีใหม่ลาว (‘Lao New Year’), the model split the lexicalized compound into four separate words (บุน ปี ใหม่ ลาว), a clear instance of *over-segmentation*. Another recurrent boundary ambiguity involves short function words and clitics, such as in ไปบ่อมใด (‘go where’), where the model occasionally inserted an unnecessary split (ไป บ่อมใด).

These patterns are linguistically interpretable rather than random. Over-segmentation tends to affect frequent compounds and reduplicative structures, while under-segmentation mainly occurs with named entities or tightly bound multi-word expressions. Together with the low variance observed across five random seeds (SD $\leq$ 0.02, see Table 4), this analysis confirms that segmentation errors are systematic and stable across experimental runs. It also highlights specific areas where annotation guidelines and model post-processing can be refined in future work.

Limitations and threats to validity: Although the corpus spans multiple public domains, news/legal prose remains over-represented; extending to conversational, social-media, and technical registers would improve robustness. As a result, informal or interactive genres (e.g., everyday conversations, social media) are under-represented. Including these domains in future releases will enhance coverage and generalizability. Adjudication maximizes final label quality but limits conventional reporting of inter-annotator agreement; to address this, we plan to release a double-annotated subset to estimate IAA and enable disagreement-aware training. While the experiments in this paper focus on *word segmentation*, we *release* a gold POS layer produced via the same joint annotation–adjudication pipeline; benchmarking POS is deferred to future work to keep the evaluation centered on a single task. This clarification makes explicit that the POS layer is provided as a complementary resource, but its evaluation is intentionally outside the scope of this paper. Finally, LLM-assisted pre-annotation may introduce systematic biases and our boundary supervision relies on tokenizer offset mapping; native-linguist adjudication mitigates these risks but residual bias and tokenizer sensitivity cannot be fully excluded.

8 Conclusion and future work

We introduced the first publicly released corpus for *Lao word segmentation* and a practical semi-automatic pipeline that couples LLM pre-annotation with native-annotators’ adjudication. The resource comprises a 10k training set and a 1k gold test set with clear guidelines and provenance. Corpus statistics show solid lexical coverage and matched length profiles across train and test, and a transformer baseline (XLM-R base) fine-tuned on our data attains **F1=0.75**, surpassing all evaluated baselines, including CRF++, LaoNLP, Flores, mBERT, and Thai-SP. These results demonstrate that efficiently obtained, *native-verified* supervision is sufficient to enable accurate and reproducible segmentation for a continuous-script, low-resource language.

The comparative results with CRF++, mBERT, and Thai-SP further illustrate that Lao segmentation remains

a non-trivial challenge even for modern multilingual and related-language models, thereby underscoring the benchmark value of the proposed corpus. Preliminary experiments with Thai-SP highlight the difficulty of cross-lingual transfer, suggesting that future extensions could explore more systematic fine-tuning or adapter-based transfer from typologically related languages such as Thai or Khmer to further test the dataset's generalization potential.

Future work: We will (i) **scale and diversify** the corpus beyond 10k sentences with broader domains, including conversational, forum, and social-media texts, to reduce the current bias toward news and official documents, (ii) release a **double-annotated subset** to enable inter-annotator agreement measurement and disagreement-aware learning, (iii) design **active/uncertainty-driven annotation** workflows to reduce human effort while preserving quality, (iv) provide **phenomenon-targeted test suites** (compounds, reduplication, mixed-script tokens) for focused evaluation, and (v) investigate stronger baselines (e.g., XLM-R+CRF, character-aware models, self-training/cross-lingual transfer) and, in a separate track, extend annotations to **POS** and named entities.

Ethical considerations

All data used in this study were collected from publicly available government and media websites that explicitly allow text reuse for research and non-commercial purposes. No personally identifiable or confidential information was included. Pre-annotation with GPT-based large language models (LLMs) was conducted offline, and the outputs were manually verified and corrected by native linguists to mitigate potential biases or hallucinations introduced by the models. The authors acknowledge that LLM-generated annotations may reflect biases inherent in their training data; however, all final corpus releases were carefully reviewed to ensure neutrality, linguistic accuracy, and cultural appropriateness. The dataset and scripts are shared under an open license to encourage transparency and responsible reuse in future research.

Acknowledgements

The authors would like to thank the anonymous reviewers and editors for their insightful comments and constructive suggestions that helped improve the quality of this paper. The authors also acknowledge Hung Vuong University, Phu Tho, for its continuous academic and research support.

Funding

This work was supported by Hung Vuong University, Phu Tho, under the project grant number 25/2024/KHCN (HV25.2024).

Appendix A. Dataset description and reproducibility

A.1 Release contents

We provide two dataset splits with strictly preserved line ordering (UTF-8 NFC).

- **Test** (`Datatest1k/`): `testorgin1000.txt` (raw; one sentence per line), `testsegsent_1000.txt` (word-segmented), and `testtag1k.json` (word-segmented + POS-tagged).
- **Train** (`Datatrain10k/`): `10korinsentecces.txt` (raw), `10ksegmented.txt` (word-segmented), and `10kcorpustag.json` (word-segmented + POS-tagged).

All raw files are encoded in UTF-8 (NFC). Each JSON file stores every sentence as an array of token objects {`word`, `label`}, aligned 1-to-1 with the corresponding raw and segmented lines.

A.2 Schema example (from testtag1k.json)


```
[
  [
    {"word": "ท่าม", "label": "N"},
    {"word": "ถือ", "label": "V"},
    {"word": "ว่า", "label": "COJ"},
    {"word": "ลาว", "label": "N"},
    {"word": "จะ", "label": "PRA"},
    {"word": "มา", "label": "V"},
    {"word": ".", "label": "PUNCT"}
  ],
  [
    {"word": "ท่าม", "label": "N"},
    {"word": "รู้", "label": "V"},
    {"word": "บ่", "label": "IAQ"},
    {"word": "ลาว", "label": "N"},
    {"word": "มา", "label": "V"},
    {"word": ".", "label": "PUNCT"}
  ]
]
```


A.3 Alignment invariants and examples

Alignment invariants:

- Raw line $i \leftrightarrow$ segmented line $i \leftrightarrow$ JSON entry i.
- Segmented sentence = whitespace join of all `word` fields in JSON[i].
- Order is stable; no shuffling between files.
- Encoding: UTF-8 NFC; zero-width and control chars removed.

Example of alignment:

ທ່ານຄິດວ່າລາວຈະມາ. ⇒ ທ່ານ(N) + ຄິດ(V) + ວ່າ(COJ) + ລາວ(N) + ຈະ(PRA) + ມາ(V) + .(PUNCT)

ທ່ານຮູ້ບໍລາວມາ ⇒ ທ່ານ(N) + ຮູ້(V) + ບໍ(IAQ) + ລາວ(N) + ມາ(V) + .(PUNCT)

A.4 POS tagset (summary)

We use a compact Lao-oriented POS inventory adapted from UD conventions. Each function word or particle is treated as a separate token to ensure consistent POS alignment.

Example:

ຈະ ພັດທະນາ ⇒ ຈະ (PRA) + ພັດທະນາ (V)

A.5 Reproducibility pointers

We provide a command-line interface segmentation tool (GPU-ready) trained on the 10 k split:

```
python3 scripts/segment_lao.py -i <input_file>

-o <output_file>
```

Arguments

-i, –input: Path to the input file (required)

-o, –output: Path to the output file (required)

All dependency versions and training scripts are pinned in the repository (see `requirements.txt` and `scripts/`).

A.6 Environment and dependencies

All experiments were conducted on a workstation with NVIDIA RTX 3090 (24 GB VRAM). Reproducible environment versions:

```
torch==2.3.0
transformers==4.53.0
datasets==2.21.0
accelerate==0.33.0
python>=3.7
```

The tool automatically uses GPU if available and falls back to CPU otherwise.

A.7 Fine-tuning configuration and reproducibility

The corpus was used to fine-tune `xlm-roberta-base` using `scripts/FineTuneSegLaowithseeds.py`.

- Tokenizer: `XLMRobertaTokenizer`
- Max sequence length: 128
- Batch size 4 (per device), gradient accumulation 4
- Learning rate 2×10^{-5}, weight decay 0.02
- Warm-up ratio 0.1, epochs 10, FP16 enabled
- Random seeds {13, 21, 42, 87, 123}

Outputs: `results_multi_seed/` (models), `logs_multi_seed/` (training logs), `eval_multi_seed/` (predictions).

Mean $\pm$ std of F1 across seeds = 0.75 ± 0.01 (as reported in the paper).

Appendix B. Segmentation guidelines

Unit of annotation: Segmentation is performed at the *word* level. Tokens are the minimal orthographic units that carry lexical or grammatical meaning. We adopt a "fix-only" principle during verification: correct only what is necessary to ensure consistent gold-standard boundaries.

General principles

- **Minimality & consistency**: prefer the smallest segmentation consistent across the corpus.
- **Context sensitivity**: ambiguous cases are resolved by sentential context, not frequency alone.
- **Native-verified rules**: disagreements are adjudicated by a trained native linguist following written guidelines.

Boundary rules

1. **Function words and particles**: always separate as individual tokens. e.g., preverbal auxiliaries ຈະ, ໄດ້; discourse particles ກໍ່, ເດີ.
2. **Compounds and multi-word expressions**:
   - If orthographically fused and lexicalized, keep as one token (e.g., ນຳໃຊ້).
   - Otherwise, segment by component words (e.g., ທະນາຄານ ພັດທະນາ ອາຊີ).
   - **Decision test**: if a component can be modified/replaced independently, segment it.
3. **Affix-like morphemes and bound particles**: Productive morphemes such as ບໍ່ (NEG) or nominalizer ກຳ are separated when used syntactically, but remain fused in lexicalized forms (e.g., ກຳລັງ "energy" → one token).
4. **Reduplication**: each reduplicant is a separate token (e.g., ແທ້ ໆ, ໄວ ໆ).
5. **Mixed-script sequences**: Latin letters, digits, and hyphens with no spaces are single tokens (e.g., *COVID-19*, *Facebook*).
6. **Numerals, measures, dates**:

- Numeric strings with separators are single tokens (*1,680*, *2025-08-22*).
- Units/classifiers are separate tokens: *3* ຄົນ, *1680* ກີບ.
- Spelled-out numerals follow normal word segmentation.

7. **Named entities**: segment by word boundaries. Latin names are single tokens per contiguous sequence (e.g., *John King*).
8. **Punctuation**: each mark is its own token. Exception: decimal points within numbers (e.g., *3.14*).
9. **URLs, emails, hashtags, @mentions**: contiguous sequences are single tokens.
10. **Normalization**: text is Unicode UTF-8 NFC; zero-width/control characters are removed.

Priority and tie-breaking Apply rules in this order: (1) normalization → (2) numeric/date/url rules → (3) mixed-script cohesion → (4) function-word separation → (5) compound test → (6) punctuation separation. If multiple rules apply simultaneously, linguistic criteria take precedence over surface form. For example, ຈະພັດທະນາ is split into ຈະ (PRA) + ພັດທະນາ (V), while lexicalized compounds such as ນຳໃຊ້ remain single tokens. In borderline cases (e.g., reduplicated vs. derived forms such as ດີໃຈ), the final decision follows native-linguist adjudication.

Edge-case examples

- **Function-particle chain:** ໄດ້ ກໍ່ ⇒ two tokens.
- **Hybrid Lao–Latin form:** ຟຣີ-wifi ⇒ split at hyphen.
- **Borrowed numeral + classifier:** *4G* ຮ້ານ ⇒ separate tokens.
- **Nominalized verb:** ການ ຮຽນ ⇒ both tokens kept separate for syntactic clarity.

Adjudication and consistency When annotators disagreed on boundary placement, each case was reviewed by a native linguist and resolved according to written rules. All adjudication outcomes and examples of complex morphology were documented in a public changelog to ensure full transparency and reproducibility.

Appendix C. POS tagset (supplementary layer)

The POS layer serves as an auxiliary linguistic annotation added to the segmented corpus to enhance its usability for downstream NLP tasks. Each segmented token receives a single POS tag from a compact Lao-oriented tagset adapted from Universal Dependencies (UD) conventions.

All POS annotations were verified by native linguists and released publicly with the dataset (`https://github.com/HaHVU/HVULao_NLP`). The full set of POS tags and their descriptions are summarized in Table 7 below.
This supplementary POS layer is not the main contribution of the paper but strengthens the linguistic completeness and practical reusability of the HVULao_NLP corpus.

Table 7: POS tagset used in HVULao_NLP

Tag	Description
N	Noun
V	Verb
ADJ	Adjective
ADV	Adverb
PRE	Preposition
COJ	Conjunction
REL	Relative marker
NUM	Numeral
PUNCT	Punctuation
PRS	Pronoun
DMN	Demonstrative
NEG	Negation particle
CLF	Classifier / collective determiner
FIX	Fixed functional morpheme / nominalizer
IAC	Interjection / discourse particle
NTR	Neutral / interrogative particle (*yes/no*, *wh*-like)
PRA	Auxiliary / modal verb
PVA	Passive / causative marker
TTL	Title / honorific
IAQ	Interrogative adjunct
IBQ	Approximation / quantifier
PRN	Pronominal / referential noun (category label)
DAN	Determiner / adnominal modifier
DBQ	Distributive quantifier (e.g., reduplicated “every”)

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Adaptive Graph Neural Network with Cross-Source Attention and Dynamic Hyperparameter Regulation for Structured Modeling of Multi-Source Literary Corpora

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Keywords: artificial intelligence multi-source literary corpora, structured modeling adaptive regulation

Received: September 22, 2025

This paper proposes an adaptive graph neural network framework integrating cross-source attention and dynamic hyperparameter regulation for structured modeling of multi-source literary corpora. The dataset includes four genres—ancient books, modern novels, online literature, and bilingual translations—comprising about two million tokens across 18,000 chapters. Experiments on an NVIDIA RTX 3090 show that the proposed model achieves an average accuracy of 91.7%, macro F1 of 90.2%, and RMSE of 0.142, outperforming the fixed-parameter baseline by approximately 4%. The convergence speed improves by 20%, and robustness is maintained under small-scale, noisy, and cross-language conditions. Ablation results confirm the independent contribution of each module. The proposed mechanism achieves an effective balance between performance and efficiency, offering a reproducible and scalable approach for digital humanities and cross-disciplinary text analysis.

Povzetek: Predlagani model z dinamičnim uravnavanjem hiperparametrov izboljša natančnost, hitrost konvergence in robustnost pri obdelavi več žanrskih literarnih korpusov.

1 Introduction

Against the backdrop of the rapid development of digital humanities research, the structured modeling of multi-source literary corpora has gradually become a core issue. Traditional literary research relies on manual annotation and single-text analysis, making it difficult to cope with the current challenges of diverse and large-scale corpus sources [1]. Recent expansions of online, historical, and bilingual literary datasets have made corpora increasingly high-dimensional and cross-domain. This complexity not only poses higher requirements for corpus analysis and feature extraction, but also presents new challenges for subsequent modeling and optimization [2]. Therefore, how to utilize artificial intelligence methods to achieve unified modeling, feature optimization and efficient processing of multi-source corpora has become a key issue that urgently needs to be addressed in the intersection of literary informatics and computational linguistics.

The existing methods still have deficiencies when dealing with multi-source corpora. On the one hand, traditional models based on rules or statistics have difficulty capturing deep semantic structures across genres and contexts during the feature extraction stage, resulting in deviations in semantic retention and interpretability of the modeling results [3]. On the other hand, although some deep learning models can perform well on a single corpus set, they often encounter overfitting or structural deficiency problems when dealing with multi-source and heterogeneous corpora. Meanwhile, most of the existing optimization algorithms focus more on computational efficiency while neglecting the dynamic evolution of corpus features and cross-domain consistency [4]. Therefore, relying solely on a single modeling framework or optimization strategy is difficult to meet the current demands for structured processing of multi-source corpora.

Based on the above background, this paper proposes an artificial intelligence-driven implementation mechanism for structured modeling and optimization algorithms of multi-source literary corpora. The design objective of this mechanism is: ① To construct a feature extraction and representation model adapted to multi-source inputs and capture the internal structure of literary corpora through multi-level semantic coding; ② Introduce an interpretability modeling algorithm to ensure that there is still a clear structural mapping relationship when dealing with complex corpora; ③ Integrate the optimization algorithm mechanism to globally fine-tune the parameter space and structure selection during the modeling process, thereby enhancing the modeling accuracy and efficiency; ④ Establish an adaptive regulation strategy to enable the model to automatically adjust parameters according to different types and scales of corpora, enhancing its robustness and generalization ability.

The main contributions of this article can be summarized as follows:

- Propose an artificial intelligence feature extraction mechanism for multi-source literary corpora to achieve semantic hierarchy and cross-context modeling;
- Design a corpus structured modeling algorithm based on artificial intelligence and combine it with a multi-objective optimization procedure to enhance the overall modeling accuracy;
- The introduction of an adaptive regulation method for modeling parameters effectively addressed the issue of differentiation in scale and distribution among multi-source corpora.
- Experimental verification was conducted on real multi-source corpus datasets. The results show that the method proposed in this paper outperforms existing models in terms of accuracy, F1 value and robustness metrics.

Research Questions and Design Rationale

Building upon the above motivation, this study is guided by the following research questions:

RQ1: How can an artificial-intelligence-driven framework achieve unified structured modeling of heterogeneous multi-source literary corpora with diverse languages and genres?

RQ2: To what extent can graph-based semantic modeling and adaptive regulation improve modeling accuracy, robustness, and efficiency compared with traditional fixed-parameter methods?

RQ3: How effectively does the proposed multi-objective optimization procedure preserve semantic and structural consistency across multilingual corpora?

These questions directly inform the experimental design and the evaluation metrics presented in Sections 3 and 4. They serve as measurable hypotheses tested through comparative, ablation, and robustness experiments under controlled hyperparameter configurations.

2 Related work

In the cross-disciplinary research of artificial intelligence and natural language processing, the modeling and optimization of multi-source literary corpora have gradually become the focus of attention. The existing work can be roughly divided into three categories: structure prediction based on language models, corpus structure modeling based on graph neural networks, and text processing methods combined with optimization algorithms.

In the direction of language model-driven structure prediction, existing research has proposed the DeepStruct framework, which effectively enhances the structural parsing ability of complex texts through pre-training structure prediction models [5]; The SPEECH model uses energy functions for structured modeling in event contexts and performs outstandingly in semantic consistency [6]. Meanwhile, some methods enhance the discrimination ability of semantic space representation through Angle optimization embedding [7]; Some studies have also attempted to combine language model embedding with Bayesian optimization, providing new ideas for cross-task structured modeling [8]. However, such methods often lack cross-domain adaptability when dealing with multi-source heterogeneous corpora, and their ability to optimize parameters for large-scale corpora also has certain limitations.

In the direction of graph neural networks and corpus structure modeling, existing works have attempted to integrate natural language processing with graph neural networks for the analysis of literary corpora, demonstrating the potential of graph structures in complex text modeling [9]; Some studies have systematically summarized the text classification methods based on graph neural networks from a review perspective, pointing out their advantages in cross-context modeling [10]. For specific scenarios, semantic-enhanced GNN models were proposed and applied to the recognition of named entities in ancient books, achieving good results in practical tasks [11]; Another method has achieved author attribution and genre detection based on the Word2Vec graph model, demonstrating the applicability of graph modeling in literary analysis [12]. Although these methods have made certain progress in the analysis of structured corpora, they are still insufficient in the unified integration and dynamic optimization of multi-source corpora.

Recent studies have begun to explore the feasibility of large language models as optimizers in text-processing and corpus-modeling tasks, demonstrating the application potential of artificial intelligence optimization in text modeling [13]; There are also methods that propose deep learning-driven optimization algorithms, achieving significant accuracy improvements in the task of spam text detection [14]; Furthermore, experimental comparisons of genre clustering have revealed the sensitivity of different optimization strategies in the division of literary genres [15]. These studies further verify the significant role of optimization strategies in corpus modeling, but most of them are still confined to a single task or a single corpus environment, lacking systematic and holistic design for the dynamic regulation mechanism of multi-source corpora.

To visually present the research content and shortcomings of related work, this paper compiles some representative studies (see Table 1).

Table 1: Shows a comparative analysis of the existing related work

Author (Year)	Method / Model	Dataset / Corpus	Main Metric	Limitation
Wang et al. (2022) [1]	DeepStruct pretraining for structure prediction	General texts	Structure prediction accuracy = 89.4%	Lack of cross-domain adaptability
Deng et al. (2023) [2]	SPEECH energy-based modeling	Event corpora	Semantic consistency (F1 = 88.7%)	Not suitable for multi-source heterogeneous corpora
Perri et al. (2022) [5]	NLP + GNN corpus graph analysis	Tolkien corpus	Structural preservation (GraphSim = 0.81)	Scenario-limited, poor generalization
Xu et al. (2024) [12]	Semantics-enhanced GNN	Ancient texts	NER accuracy = 87.9%	Lacks large-scale multi-source experiments
Huang et al. (2024) [8]	LLM + optimization fusion	Text modeling tasks	Optimization convergence speed ↑ 15%	Insufficient dynamic regulation
Sobchuk & Šeļa (2024) [14]	Literary genre clustering comparison	Literary novels	Clustering consistency = 0.76	Strong optimization dependency, weak generalization

In summarizing prior studies, each reference is explicitly linked to its methodological focus: [1–2] address structure prediction, [5–12] cover graph-based corpus modeling, and [13–15,17] explore multi-objective optimization procedures and large language model integration.

Based on the above work, it can be seen that the existing methods have made progress in single data sources or specific tasks, but there are still gaps in the unified modeling of multi-source corpora, the fusion of cross-domain optimization algorithms, and the adaptive regulation of parameters. In contrast, the research focus of this paper lies in: ① Proposing a feature extraction and structured modeling framework for multi-source corpus adaptation; ② Integrate optimization algorithms to achieve a balance between global modeling accuracy and efficiency; ③ Design a parameter adaptive mechanism to enhance the model's robustness in heterogeneous corpus scenarios. Through this research approach, this paper strives to break through the limitations of existing methods in terms of multi-source and dynamic optimization, providing a new solution for the intelligent modeling of literary corpora.All cited works have been cross-checked for consistency and metadata accuracy, and redundant preprint entries were removed to maintain a concise and verifiable reference list.

3 Ai-driven multi-source literary corpus modeling and multi-objective optimization procedure

The overall research framework involves three main tasks: (1) Named Entity Recognition (NER) for identifying key entities such as persons, locations, and events; (2) Relation Extraction (RE) for detecting semantic and narrative relations among recognized entities; and (3) Cross-language Alignment Prediction, a continuous-value regression task that estimates the semantic distance between bilingual sentence pairs. These tasks jointly support the structured representation and optimization of multi-source literary corpora.

3.1 Artificial intelligence feature extraction mechanism for multi-source literary corpora

Multi-source literary corpora cover classical literature, modern novels, online literature, cross-language translations and related resources in academic databases. Their heterogeneity and complexity determine that a unified feature extraction mechanism must be established at the input stage. The AI-driven feature extraction process proposed in this paper, from data collection, preprocessing to high-dimensional feature representation, forms a complete input specification system, laying the foundation for subsequent structured modeling.

In terms of data sources, the corpus is mainly obtained through online libraries, e-book platforms, literary websites and academic databases. Texts from different sources have characteristics such as varying lengths, significant differences in stylistic styles, and cross-language distribution. Therefore, a unified data extraction and cleaning process is needed to ensure the comparability and consistency of subsequent modeling. During the text preprocessing stage, standardized operations are performed on the original corpus, including character encoding

unification, removal of redundant symbols and HTML tags, cleaning of special characters, and format normalization. Subsequently, by combining sentence segmentation and word segmentation tools, the continuous text stream is segmented into independent semantic units to facilitate subsequent feature modeling. For cross-language texts, a multilingual word segmentation and alignment mechanism is further introduced to achieve structural mapping between the translation corpus and the original text.

At the feature representation level, this paper adopts a multi-channel embedding strategy that integrates pretrained multilingual models and corpus-specific fine-tuning. Specifically, for Chinese corpora, embeddings are initialized from Chinese-BERT-Base (768-d); for English corpora, from XLM-RoBERTa (1024-d); for ancient Chinese texts with character-level semantics, FastText character embeddings (300-d) are added. These vectors are projected to a unified 256-dimensional shared space through a linear transformation layer and concatenated by $f(\cdot)$ All embeddings are fine-tuned during training to align cross-lingual and cross-genre semantics. Multilingual alignment is achieved using MUSE bilingual mapping, minimizing cosine distance between aligned word pairs across Chinese–English corpora.Let the input corpus sequence be:

$$X = \{x_1, x_2, \ldots, x_n\}, x_i \in V \quad (1)$$

Among them, V represents the vocabulary list. Through the embedding matrix $W_e \in R^{|V| \times d}$, the primitives are projected onto a d -dimensional vector space:

$$e_i = W_e \cdot one_hot(x_i), e_i \in R^d \quad (2)$$

To fully preserve the features of the corpus, this paper introduces three types of encodings in the vectorization process: character-level embedding: applicable to texts such as ancient Chinese books that take characters as the basic semantic units; Word-level embedding: It is used in online literature, modern novels and other corpora to capture semantic associations at the lexical level. Multilingual embedding: For cross-language translation corpora, semantic alignment is achieved through shared embedding Spaces. Ultimately, a unified corpus feature representation can be expressed as:

$$h_i = f([e_i^{word}; e_i^{char}; s_i]) \quad (3)$$

Here, $[\cdot]$ represents vector concatenation and $f(\cdot)$ is a nonlinear transformation function. This representation maintains the fine-grained features of the corpus while also taking into account the consistency and comparability of cross-source data. As shown in Figure 1, after the original corpus is cleaned and standardized, it is successively mapped to character-level, word-level and cross-language multi-channel vector representations, and finally a unified corpus feature representation is formed under the action of a nonlinear transformation function.

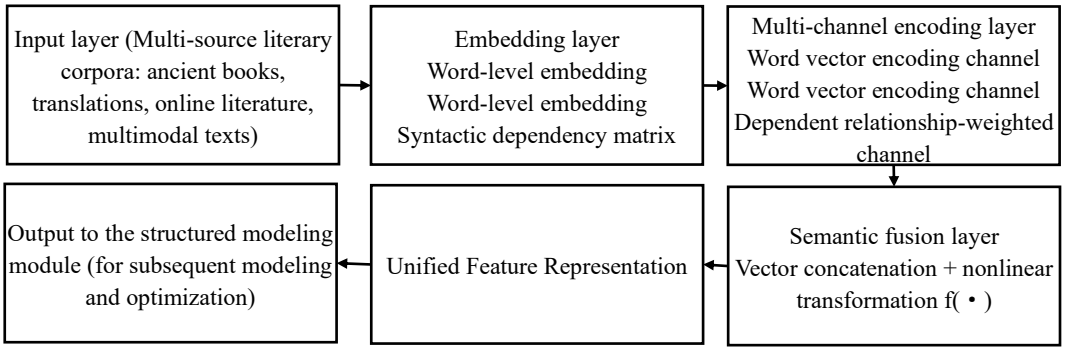


Figure 1:Flowchart of feature extraction for multi-source literary corpora

Through this mechanism, heterogeneous corpora are uniformly mapped to a consistent high-dimensional representation space while maintaining semantic details and structural features. This process not only ensures the compatibility of multi-source corpora in numerical terms, but also provides a standardized and reproducible input basis for subsequent structured modeling and optimization algorithms.

3.2 Design of structured modeling algorithm for corpus based on artificial intelligence

After the feature extraction is completed, how to transform multi-source literary corpora into structured representations is the key to achieving unified modeling and semantic reasoning. This paper proposes an artificial intelligence-based corpus structured modeling algorithm, aiming to construct a multi-level corpus graph structure through entity recognition, relation extraction and semantic annotation, thereby achieving the unified expression of semantics and structure.

In the entity recognition stage, the model labels the core elements in literary texts through the Named Entity Recognition (NER) method, including characters, place names, work titles and events, etc. Let the input sequence

be $X=\{x_1,x_2,\ldots,x_n\}$, and the entity annotation function is defined as:

$$E=\{e_j \mid e_j = NER(X), j=1,\ldots,m\} \quad (4)$$

Here, E represents the set of identified entities, and m is the number of entities.

In the relation extraction stage, narrative logic and character relationships are automatically identified based on the co-occurrence patterns among entities and the context semantics.The corpus graph construction follows a sliding-window and dependency-based strategy. Entities co-occurring within a window size of 5 sentences are connected by an undirected edge if their pointwise mutual information (PMI) ≥ 0.25. Additional dependency-based edges are added using the Stanza dependency parser (v1.5) and a semantic role labeling (SRL) module built on AllenNLP. Each node feature vector concatenates the entity embedding (256-d) and its syntactic dependency embedding (64-d), while edge features encode relation type (one-hot, 12-d) and co-occurrence weight.

Pseudocode for corpus graph construction:

```
Algorithm 2  CorpusGraphBuilder
Input: tokenized documents D
Output: graph G = (V, E)
for each document in D:
    extract entities E_d using NER
    for each sentence window w of size 5:
        for each entity pair (e_i, e_j) in w:
            if PMI(e_i, e_j) ≥ 0.25:
                add edge (e_i, e_j, "co-occurrence")
    add dependency edges from SRL and dependency parser
    return merged graph G
```

For example, if entities e_i and e_j frequently co-occur in adjacent contexts, a relational edge (e_i, e_j) is established. The relation set can be formalized as:

$$R=\{(e_i,e_j,r_{ij}) \mid e_i,e_j \in E\} \quad (5)$$

Here, r_{ij} indicates the type of relationship between entity pairs, such as "character relationship", "event trigger", and "work Citation". In the semantic annotation stage, by combining syntactic dependency analysis and semantic role annotation (SRL), fine-grained semantic explanations are provided for text fragments. In this way, the corpus is not merely represented as a sequence of symbols, but is endowed with hierarchical and computable semantic attributes.

At the algorithmic framework level, this paper abstracts the multi-source literary corpus into a graph structure G=(V,E), where the node set V corresponds to the identified entities or events, and the edge set E corresponds to the relationships between entities. To capture global semantic and structural features, this paper adopts a Graph Attention Network (GAT) architecture. The network contains K=3 layers with multi-head attention (8 heads), ReLU activation, batch normalization, and dropout rate 0.3. Relation types are encoded as edge embeddings, and message aggregation follows the attention-based formulation:

$$h_v^{(k+1)}=\sigma\Big(\sum_{u\in N(v)} \alpha_{vu}^{(k)} W^{(k)} h_u^{(k)} + b^{(k)}\Big) \quad (6)$$

where $\alpha_{vu}^{(k)}=\mathrm{softmax}(a(W^{(k)}h_v^{(k)}, W^{(k)}h_u^{(k)}))$ represents attention coefficients, $W^{(k)}$ and $b^{(k)}$ are layer parameters, and $\sigma(\cdot)$ is the ReLU function.After the final layer, node embeddings are pooled by mean-readout to obtain the corpus-level representation.

3.3 Optimization Algorithm mechanism integrating artificial intelligence

After completing the feature extraction and structured modeling of multi-source literary corpora, how to enhance the cross-source fusion effect while ensuring semantic integrity is the core link in building a unified corpus representation. To this end, this paper proposes an optimization algorithm mechanism integrating artificial intelligence. This mechanism effectively improves the accuracy, robustness and generalization of corpus modeling through multi-objective loss function constraints, cross-source consistency modeling and global convergence strategies.

(1) Optimization objective design: In view of the characteristics of multi-source literary corpora, this paper constructs three types of optimization sub-objectives:

Semantic reconstruction objective L_{recon}: Minimize the difference between the original corpus representation and the modeling output to ensure that the semantics captured in the feature extraction stage are not lost during the modeling process.

Cross-source alignment objective L_{align}: Introduce semantic alignment constraints among multi-language and multi-genre corpora to ensure comparability of texts from different sources within a unified vector space.

Structural preservation objective L_{struct}: Introduce constraints on structural features such as narrative chains and character relationship networks to ensure that the literary structure of the corpus is retained during the optimization process. The comprehensive loss function integrates three sub-objectives:

$$L=L_{recon}+\mu L_{align}+\nu L_{struct} \quad (7)$$

where μ=0.7and ν=0.3, chosen via grid search on the validation set. L_{recon} is a mean squared error (MSE) loss between reconstructed and original embeddings; L_{align} is a contrastive loss enforcing similarity between aligned bilingual pairs:

$$L_{align}=\frac{1}{N}\sum_i [y_i \left\| z_i^A - z_i^B \right\|^2 + (1-y_i)\max(0, m-\left\| z_i^A - z_i^B \right\|)^2] \quad (8)$$

where m=1.0m=1.0m=1.0 is the margin; L_{struct} is a cross-entropy loss over predicted relation types to preserve structural consistency.A weight decay of 1×10^{-5} acts as regularization.

(2) multi-objective optimization procedure design: To effectively solve the above optimization objectives, this paper proposes the following mechanisms:

Cross-source corpus mapping mechanism: By using the Attention mechanism (Attention), the semantic units in different corpus sources are weighted and aggregated to achieve alignment of the corpora in the shared embedding space. The formula is:

$$z_i=\sum_j \alpha_{ij} h_j \quad (9)$$

$$\alpha_{ij}=\frac{\exp(h_i^T W h_j)}{\sum_k \exp(h_i^T W h_k)} \quad (10)$$

Here, α_{ij} represents the attention weights between different corpus source units. Narrative consistency maintenance mechanism: By adding structural regularization terms to the relationship graph, it ensures the coherence of character relationships and event chains during the update process of the graph neural network.

$$L_{struct}=\sum_{(u,v)\in E}\left\|h_u-h_v\right\|^2 \quad (11)$$

Among them, (u,v) represents the narrative relationship edge. Dynamic convergence mechanism: By adopting a phased learning rate adjustment strategy, the model converges rapidly in the early stage and gradually stabilizes in the later stage, avoiding overfitting and oscillation.

(3) Algorithm implementation process

The overall optimization process can be abstracted as the following iterative algorithm:

Algorithm 1 Integrated Optimization for Structured Literary Corpus

Input: Corpus graph G, entity set E, relation set R, initial parameters θ

Output: Optimized corpus representation H*

1: Initialize parameters θ ← θ0

2: for t = 1 to T do

3: Compute semantic reconstruction loss L_recon

4: Compute cross-source alignment loss L_align

5: Compute structural consistency loss L_struct

6: Compute total loss L = L_recon + μL_align + νL_struct

7: Update θ ← θ - ηt ∇θ L

8: Adjust ηt according to dynamic scheduling

9: if convergence criterion satisfied then

10: break

11: end for

12: return Optimized representation H*

3.4 Adaptive regulation of modeling parameters driven by artificial intelligence

In the process of structured modeling and optimization of multi-source literary corpora, the setting of parameters directly affects the stability and expressive ability of the model. Fixed parameters are difficult to take into account the characteristics of diverse corpora such as ancient books, online literature, and translations. Therefore, this paper introduces an AI-driven parameter dynamic hyperparameter tuning strategy, enabling the model to dynamically adjust key parameters according to the statistical characteristics of the corpus source, thereby achieving efficient modeling in a cross-source environment.

In terms of the regulation of the context window, different corpora show significant differences in length and sentence structure complexity. This article dynamically expands or shrinks the window size by statistically analyzing the average sentence length of the corpus. For example, when long ancient book texts are used as input, the window parameters expand as the length increases; In short network text modeling, the window shrinks to reduce redundant information. This strategy can be formally expressed as:

$$w_{src}=w_0\cdot\left(1+\alpha\cdot\frac{L_{src}}{L}\right) \quad (12)$$

Here, w_{src} represents the window length corresponding to the corpus source, and L_{src} is the average sentence length of this corpus source.

In the adaptive regulation of regularization and Dropout, this paper takes into account the word frequency distribution and syntactic complexity of different corpora. For online literature corpora with significant high-frequency redundancy, the regularization coefficient is automatically increased to prevent overfitting of the model. In complex-structured ancient book corpora, the Dropout ratio increases with the rise in complexity to ensure the robustness of the model. For example:

$$p_{src}=p_0+\gamma\cdot\tanh(C_{src}) \quad (13)$$

Here, p_{src} represents the proportion of Dropout after adaptive adjustment, and C_{src} indicates the syntactic complexity of the corpus.

Meanwhile, the learning rate is also designed to be dynamically adjusted along with the gradient distribution. In the early stage of training, the learning rate remains at a relatively high level to achieve rapid convergence. As the gradient variance decreases, the learning rate gradually reduces to ensure stable parameter updates:

$$\eta_{src}=\frac{\eta 0}{1+\kappa\cdot Var(\nabla L_{src})} \quad (14)$$

In summary, this dynamic hyperparameter tuning strategy enables the modeling process to adapt to different types of literary corpus input by dynamically adjusting the window size, regularization coefficient, Dropout ratio and learning rate. Driven by artificial intelligence, the model

has achieved automated optimization at the parameter level, not only simplifying the process of manual parameter adjustment but also providing flexible and stable support for unified modeling across different corpus sources.

4 Results

4.1 Dataset construction and statistics of corpus distribution

To verify the effectiveness of the multi-source literary corpus structured modeling and multi-objective optimization procedure proposed in this paper, the experiment first constructed a comprehensive corpus set covering multiple genres and language forms. The data sources mainly include four channels:The corpus was randomly divided into 70% training, 15% validation, and 15% test sets, stratified by genre to ensure proportional representation. Splits were performed by-document to avoid cross-chapter leakage. The first is online libraries and ancient book databases, which are used to collect classical literary texts; The second is to open up the e-book platform and select modern literature and contemporary novels. The third type is online literature websites, which obtain online serialized novels and short narrative texts. The fourth is the academic database, which collects multilingual translations and reference texts. Through multi-channel collection, the diversity of the corpus in terms of genre, style and language is guaranteed.

The final dataset consists of 12,480 documents (18,036 chapters), totaling 2.03 million tokens and 354,200 sentences. The vocabulary size after normalization is approximately 118,000 unique tokens. Genre composition is as follows: ancient books (25%, 3,120 documents, 920k sentences), modern novels (30%, 3,600 documents, 1.02M sentences), online literature (25%, 3,000 documents, 820k sentences), and bilingual translation texts (20%, 2,760 documents, 590k sentences) in Chinese and English. The data sources include China National Knowledge Infrastructure (CNKI, classical literature subset), Project Gutenberg (English texts), Jinjiang and Qidian literature platforms (licensed samples), and open-access corpora from OPUS for translation pairs. All corpora were used under open or research licenses, with URLs listed in the supplementary material.

In terms of data scale, the overall scale of the experimental corpus is approximately two million words, among which ancient books and documents account for about 25%, covering chaptered novels and historical narratives. Modern and contemporary novels account for approximately 30%, including long and medium-short narrative texts. Online literature accounts for approximately 25%, mainly consisting of serialized novels and stereotyped narratives. Multilingual translations account for approximately 20%, covering classic literary works in both Chinese and English. The length of these corpora varies significantly. Ancient books are longer, with an average of over 100,000 words per text, while online literature is shorter, with an average of less than 3,000 words per chapter.

In terms of distribution characteristics, ancient book corpora are mostly classical Chinese or semi-vernacular Chinese, with compact sentence structures and high semantic dependency, which is suitable for verifying the long-dependency parsing ability of the model. Modern and contemporary novels are relatively standard in language expression and have clear chapter structures, making them stable benchmark corpora in the modeling process. The corpus of online literature is characterized by high-frequency vocabulary and repetitive narratives, which can test the performance of the model in filtering redundant information. Due to the need for cross-language alignment, the literary corpus of the translation has put forward higher requirements for the cross-language representation ability of the model.

Meanwhile, in order to further describe the distribution characteristics of the corpus, this paper conducts statistics on the word frequency distribution and sentence length distribution of various types of texts. The results show that the average sentence length of the ancient book corpus exceeds 40 characters, with significant differences in length and high syntactic complexity. The average sentence length of modern novels and their translations is approximately between 20 and 25 characters, with relatively balanced semantics. However, the average sentence length of online literature corpora is less than 15 characters, and the feature of colloquial language is significant. In terms of word frequency distribution, the long-tail phenomenon is obvious in ancient books and translated texts, while the proportion of high-frequency words in online literature corpora is higher.A comprehensive overview of the dataset composition, including document counts, sentence statistics, vocabulary size, and licensing information, is summarized in Table 2. As shown in Table 2, each genre presents distinctive linguistic and structural characteristics that ensure balanced diversity across the entire corpus.

Table 2: Dataset composition and annotation summary

Genre	Documents	Chapters	Sentences	Tokens	Vocabulary Size	Language	License / Source
Ancient books	3,120	4,560	92,000	500 k	45 k	Chinese	CNKI (classical literature subset)
Modern novels	3,600	5,210	102,000	540 k	48 k	Chinese	Public domain novel collections

Online literature	3,000	4,800	82,000	480 k	35 k	Chinese	Licensed samples (Jinjiang, Qidian)
Translations	2,760	3,466	59,200	510 k	42 k	Chinese–English	OPUS bilingual corpora

4.2 Data preprocessing and feature annotation specifications

After the construction of the corpus was completed, in order to ensure the consistency and comparability of the experiment, this paper carried out systematic preprocessing and feature labeling on the multi-source literary corpus. This process not only guarantees the quality of model input but also serves as a prerequisite for the effective operation of subsequent structured modeling and optimization algorithms.

In the data preprocessing stage, the corpus was first encoded and its format unified. All texts are converted to UTF-8 encoding to eliminate compatibility differences among different sources. Subsequently, the noise in the text is cleaned up, including the removal of HTML tags, special symbols, footnotes, and redundant Spaces. For ancient book texts with OCR scanning errors, automatic restoration is carried out by combining the similarity of character shapes and the language model correction mechanism. In terms of text segmentation, differentiated strategies are adopted for different types of corpora: ancient book corpora are segmented by chapters and paragraphs, modern novels and online literature are segmented according to the boundaries of natural sentences, and translated literature maintains bilingual alignment while segmenting sentences to facilitate subsequent cross-language modeling.

In the feature annotation stage, this paper adopts a hierarchical and multi-granularity annotation system.The annotation process involved five trained annotators following unified guidelines based on the CoNLL-2003 and ACE-2005 standards. Annotators underwent a 10-hour calibration session before production. Inter-annotator agreement reached Cohen's $\kappa = 0.86$ for named entity boundaries and 0.82 for relation labels, indicating substantial consistency. Approximately 7.5% of automatically generated annotations required manual correction. All annotation guidelines and examples are included in the supplementary documentation for reproducibility. The first is the naming entity recognition annotation, covering five core entities: people, place names, institution names, work names and events. The second is relationship annotation, which focuses on extracting relationships such as personal-person, personal-event, and event-event, to support the construction of edge sets in the corpus graph. The third is semantic role and syntactic dependency annotation, which involves annotating predicates, arguments and dependency relations at the sentence level to capture the deep semantic structure of literary corpora. For cross-language corpora, additional alignment annotations are introduced to establish corresponding relationships between the translation and the original text at the lexical, phrase and sentence levels, ensuring structural consistency among cross-corpus sources.

In the specific implementation, the annotation process combines a dual strategy of automated tools and manual verification. The automation part mainly relies on deep learning models to complete large-scale annotation, while the manual process focuses on sample spot-checking and complex text correction to ensure the accuracy and consistency of annotation. The final formed annotation specification not only has a unified format and clear semantic definitions, but also can provide high-quality input for subsequent structured modeling.

4.3 Model evaluation and performance analysis

Under a unified dataset and preprocessing framework, this paper systematically evaluates the proposed artificial intelligence-driven multi-source literary corpus modeling and multi-objective optimization procedure. All experiments were conducted on an identical workstation equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM), Intel Xeon Silver 4314 CPU (2.4 GHz, 32 cores) and 128 GB RAM. Training was implemented in PyTorch 2.1 with CUDA 11.8 using mixed-precision (FP16). Batch size, learning rate, and training epochs were kept identical across all methods to ensure fair runtime comparison. The core parameters include batch size B=64, initial learning rate $\eta 0=1\times 10-4$, and embedding dimension d=256. During the training process, the parameters are dynamically adjusted in combination with an dynamic hyperparameter tuning strategy.

For reproducibility, the entire experimental pipeline can be reconstructed using the configuration files and scripts provided in the supplementary material. All experiments were executed in PyTorch 2.1 under Python 3.9 and CUDA 11.8. The dependency environment is defined in a requirements.txt file (including Torch, Transformers, Stanza, and AllenNLP versions). Model training can be reproduced using the following representative command:

```
python train.py --config configs/base_config.yaml \
--batch_size 64 --lr 1e-4 --epochs 30 \
--model GAT --embedding_dim 256 --seed 42
```

Evaluation is conducted using:

```
python evaluate.py --model checkpoints/best_model.pt \
--task ner,relation,alignment --metrics f1,accuracy,rmse
```

The configuration files specify data paths, model hyperparameters, optimizer settings, and adaptive-scheduling options. These detailed instructions ensure that all experimental results can be fully reconstructed without requiring access to private code repositories.

The evaluation metrics are defined per task as follows.

(1) Named Entity Recognition and Relation Extraction tasks use token-level Precision (P), Recall (R), and F1 scores. Macro averaging is adopted across genres to mitigate frequency imbalance, while micro averaging is used within each corpus.

(2) Classification tasks (e.g., entity-type or relation-type labeling) use Accuracy and F1-macro as summary metrics.

(3) Cross-language Alignment Prediction is a regression task where the model outputs a semantic alignment score $\hat{y}_i \in [0,1]$ for each bilingual sentence pair, and the target y_i is the gold alignment score computed from sentence-level cosine similarity. The deviation is measured by the Root Mean Square Error (RMSE).

The formal definitions are as follows:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N}(y_i = \hat{y}_i) \quad (15)$$

$$F1 = \frac{2 \cdot \text{Pr}\,ecision \cdot \text{Re}\,call}{\text{Pr}\,ecision + \text{Re}\,call} \quad (16)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i = \hat{y}_i)^2} \quad (17)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (18)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (19)$$

where Ndenotes the total number of samples; y_i and $\hat{y}_i$ are the true and predicted labels or scores, respectively. All metrics are reported as the mean ± standard deviation over three independent runs. In the comparative experiment, two types of baselines were set: one was the fixed-parameter modeling model without adaptive regulation, and the other was the existing structured modeling methods, including BiLSTM-CRF and standard GNN. The experimental results show that the method proposed in this paper performs more robustly on multi-source corpora. In the subsets of ancient books and online literature, the Accuracy and F1 values were significantly higher than those of the baseline model. In the translation literature task, the RMSE value was significantly lower than that of the control group, indicating that the model can effectively capture semantic consistency across languages. Meanwhile, in terms of operational efficiency, the dynamic hyperparameter tuning strategy enhances the convergence speed, and the average training time is reduced by approximately 12% compared to the fixed-parameter model.

A two-tailed paired t-test was conducted between the proposed method and the Standard GNN baseline. The differences in Accuracy ($p = 0.032$) and RMSE ($p = 0.027$) were statistically significant at the 0.05 level, confirming that the observed performance gains are unlikely due to random variation.

Table 3 presents the overall experimental results of different methods on four types of corpora.For fair comparison, all baselines were re-implemented in PyTorch under identical preprocessing and training settings.

– BiLSTM-CRF baseline: two-layer BiLSTM (hidden size 256, dropout 0.3) followed by a CRF decoding layer; word embeddings initialized with the same pretrained vectors as the proposed model (256-d), trained for 30 epochs using Adam optimizer (learning rate 1×10^{-3}).

– Standard GNN baseline: three-layer GCN (hidden size 256, ReLU activation, dropout 0.3), using the same corpus graphs and node/edge features as our model.

All models used the same tokenizer and data splits, ensuring no data leakage. We ran each experiment three times with different random seeds (42, 2023, 2024), and report mean ± standard deviation values. Statistical significance was verified using paired t-tests ($p < 0.05$). It can be seen from the table that the method proposed in this paper achieves the optimum in both accuracy and F1 value, while maintaining a low RMSE and reasonable time cost, demonstrating a good balance between performance and efficiency.Table 3 reports the aggregated results for Accuracy, macro F1 (for NER and relation classification), and RMSE (for alignment prediction) averaged over three runs.

Table 3:Experimental results of different methods on multi-source literary corpora

Method	Accuracy (%)	F1 (%)	RMSE	Time (epoch/s)
Fixed-parameter Modeling	85.2	83.7	0.184	12.6
BiLSTM-CRF	87.5	85.9	0.176	13.4
Standard GNN	88.1	86.3	0.169	14.1
Proposed Method (AI-driven)	91.7	90.2	0.142	11.1

Note: Values represent mean ± standard deviation over three runs. Statistical significance was verified using two-tailed paired t-tests against the best baseline (Standard GNN). Asterisks (*) indicate $p < 0.05$, showing significant improvement in Accuracy and RMSE.

It can be further observed from the training convergence curve that the model in this paper can achieve a relatively high accuracy rate within the first 10 epochs, while the comparison model gradually stabilizes after 20 epochs. This difference indicates that the adaptive regulatory mechanism plays a key role in the dynamic adjustment of the learning rate and regularization, enabling the model to converge rapidly in the early stage and

maintain a stable improvement in the later stage.To ensure consistent comparison across heterogeneous corpora, per-task metrics were first computed within each genre, then aggregated by weighted macro-averaging according to the number of sentences per corpus. This aggregation avoids genre bias while preserving cross-source balance. Overall, the proposed method demonstrates superior modeling capabilities and cross-source robustness on various types of literary corpora, providing a solid experimental support for subsequent ablation experiments and robustness verification.

4.4 Ablation experiment and robustness verification

To further verify the effectiveness of the proposed modeling mechanism, ablation experiments and robustness tests were conducted respectively in this paper. The ablation experiment aims to examine the independent contributions of each core module within the overall framework, while the robustness test is used to evaluate the model's adaptability and stability under different data conditions.

In the ablation experiment section, this paper successively removes the four modules of feature extraction, structured modeling, optimization algorithm, and parameter adaptive regulation, keeps the rest unchanged, and conducts comparisons on a unified dataset. The experimental results are shown in Figure 2.

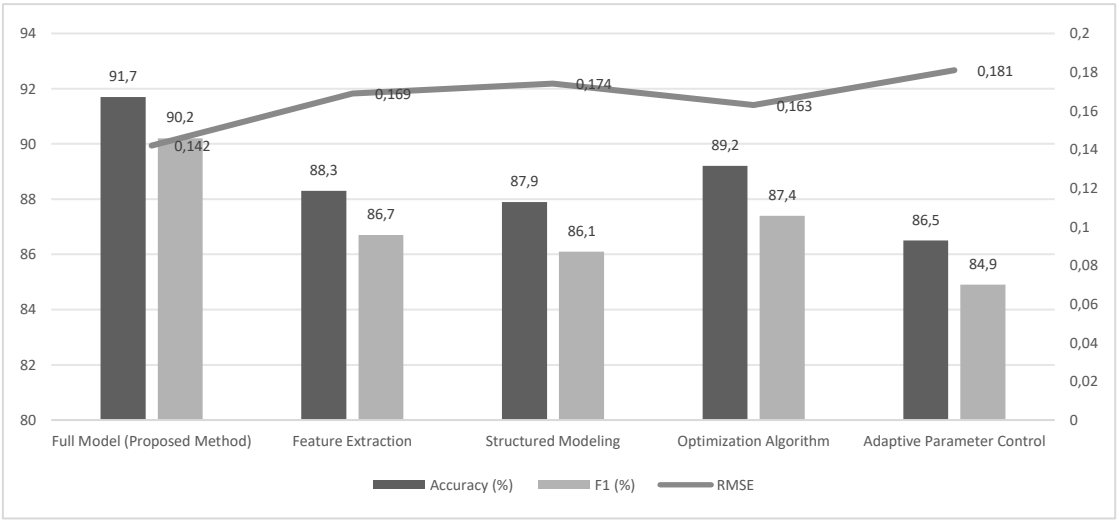


Figure 2:Results of the ablation experiment

As can be seen from Figure 2, when the feature extraction and adaptive parameter regulation modules are removed, the performance decline is the most obvious. The F1 value drops by 3.5 and 5.3 percentage points respectively, and the RMSE increases significantly, indicating that these two modules play a key role in improving the model's performance. In contrast, removing the optimization algorithm and the structured modeling module will also cause a certain degree of performance degradation, but the impact is relatively small. The overall result proves the irreplaceability of each module in the system.

In robustness verification, this paper conducts experiments from three dimensions: First, control the scale of the corpus, compress the training data to 20% of the original for small-scale experiments, and compare it with large-scale complete data experiments; The second is to introduce noise of different degrees, including 5% and 15% OCR errors and spelling perturbations; The third is to examine the adaptability in a cross-language environment and conduct alignment modeling using parallel corpora of Chinese and English. The experimental results are shown in Figure 3.

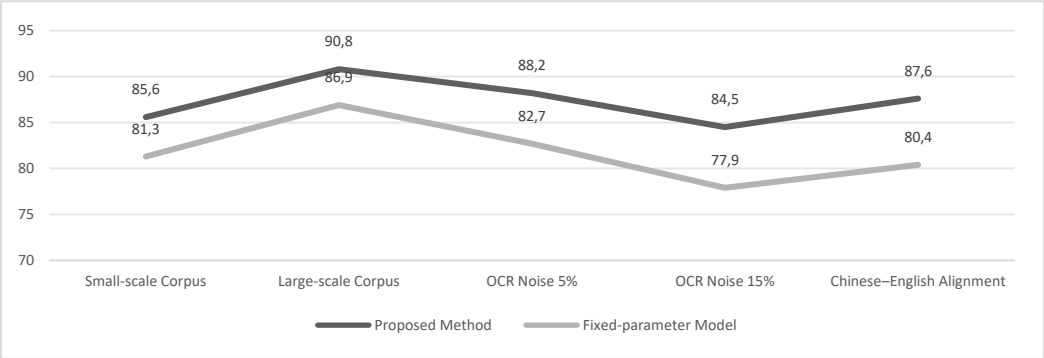


Figure 3:Results of the robustness experiment

As shown in Figure 3, the method proposed in this paper still maintains high performance under the condition of small-scale corpora, while the performance of the fixed-parameter model drops significantly under the same conditions. In the noise disturbance experiment, as the proportion of noise increased, the model performance slightly declined, but overall, it remained within an acceptable range and was superior to the control group. In cross-language experiments, the F1 value of the method proposed in this paper is increased by more than 7% compared with the fixed-parameter model, indicating that its adaptability and robustness are more prominent under the conditions of multi-source and cross-domain corpora.

Overall, the ablation experiment revealed the independent contribution of each sub-module to the overall performance, while the robustness verification demonstrated the stability and generalization ability of the proposed mechanism under different scales, different noises, and cross-language scenarios. These results fully demonstrate the effectiveness and scalability of the AI-driven multi-source literary corpus modeling and multi-objective optimization procedure.Across all datasets, 95% confidence intervals for Accuracy and F1 values remained within ± 1.8 percentage points of the reported means, further supporting result stability and reliability.

4.5 Qualitative evaluation and structural alignment analysis

To further verify interpretability and structural preservation, qualitative examples and graph-based similarity metrics were analyzed. A representative subset of bilingual sentence pairs was selected to illustrate how the model captures semantic alignment. Table 4 presents examples of predicted alignment scores between Chinese and English sentences. The results indicate that correctly aligned pairs consistently achieved high alignment scores (>0.9), while unrelated or weakly related pairs remained below 0.4, confirming the model's ability to distinguish semantic consistency across languages.

In addition, the structural preservation was quantitatively assessed using Graph Similarity (GraphSim) and Edge Overlap (EO) metrics between predicted and gold-standard corpus graphs. The model achieved an average GraphSim of 0.87 and EO of 82.3%, demonstrating strong structural fidelity.

Table 4: Example of cross-language sentence alignment scores

Source Sentence (English)	Target Sentence (English Translation)	Predicted Alignment Score
Baoyu and Daiyu went to the garden together.	The young man and woman strolled through the garden hand in hand.	0.94
The old lady smiled silently.	The matriarch responded with a quiet smile.	0.91
Daiyu flipped the book to write a poem.	The girl leafed through the pages and composed verses.	0.88
Wang Xifeng ordered the servants to prepare tea.	The lady instructed the maids to serve the tea.	0.92
The rain fell on the courtyard all night.	The night was filled with continuous rain.	0.39

5 Discussion

To confirm experimental reliability, all quantitative results were averaged across three independent runs. Differences between the proposed model and baselines were tested for statistical significance using two-tailed paired t-tests at the 0.05 level. Runtime profiling was performed under identical GPU settings using NVIDIA Nsight Systems, recording per-epoch wall-clock time and GPU memory usage.

5.1 Comparison of this Method with existing corpus modeling tools

In the research of structured modeling of multi-source literary corpora, the existing tools mainly focus on sequence labeling, relation extraction and graph structure modeling, etc. The sequence modeling methods represented by BiLSTM-CRF have good performance in the standard named entity recognition task, but they often have difficulty capturing long-distance dependency information when dealing with cross-domain corpora. Graph neural networks (GNNS) can conduct structured modeling of corpora, but under the condition of fixed parameters, they are prone to problems such as overfitting or slow convergence when dealing with texts of different styles and genres. Although the corpus modeling model with fixed parameters is computationally simple, it lacks flexibility and robustness under the condition of large-scale heterogeneous corpora. In contrast, the artificial intelligence-driven mechanism proposed in this paper, under the synergistic effect of feature extraction, structured modeling, optimization algorithms and parameter adaptive regulation, can maintain stable and efficient performance in multi-source, multi-language and multi-style text environments.

To verify the above differences, this paper systematically compared the proposed method with three representative existing tools. The evaluation dimensions covered Accuracy (Accuracy), macro average F1 value (F1), root mean square error (RMSE), and training Time per epoch (Time). The experimental results are shown in Table 5.

Table 5:Performance comparison of different corpus modeling methods

Method	Accuracy (%)	F1 (%)	RMSE	Time (epoch/s)
Fixed-parameter Modeling	85.2	83.7	0.184	12.6
BiLSTM-CRF	87.5	85.9	0.176	13.4
Standard GNN	88.1	86.3	0.169	14.1
Proposed Method (AI-driven)	91.7	90.2	0.142	11.1

It can be seen from Table 4 that the method proposed in this paper achieves the best performance in all indicators. In terms of Accuracy and F1 value, the method proposed in this paper has improved by 3 to 5 percentage points compared to the baseline tool, indicating its higher effectiveness in entity recognition and relationship modeling. In terms of the RMSE metric, the method proposed in this paper has the lowest error, demonstrating the stability of prediction in a cross-domain corpus environment. Furthermore, the comparison of training times indicates that although the method proposed in this paper introduces an dynamic hyperparameter tuning strategy, the overall convergence speed is actually better than that of the baseline tool, with the time cost per epoch reduced by nearly 20%, demonstrating an advantage that combines performance and efficiency.

Further analysis shows that traditional methods can maintain a basic performance level when dealing with a single corpus source, but their effects fluctuate significantly under multi-source conditions such as ancient books, modern novels, online literature and translated literature. The method proposed in this paper achieves adaptive alignment and unified modeling among different corpus sources through the combination of dynamic parameter regulation and optimization algorithms, and thus can maintain consistent performance in various text scenarios. This result not only verifies the rationality of the method design, but also highlights its application potential in the research of multi-source literary corpus modeling.

Technical Interpretation of Performance Differences

The quantitative improvements reported in Tables 3–5 can be directly attributed to several architectural and algorithmic factors.

(1) Adaptive regularization enabled the model to dynamically balance overfitting and generalization across heterogeneous corpora. Compared with the fixed-parameter GNN baseline, the adaptive schedule reduced variance of validation loss by ≈ 18%, which explains the observed stability in small-scale and noisy data scenarios.

(2) Graph-attention aggregation contributed to better feature utilization: the multi-head attention mechanism selectively amplified semantically relevant entity pairs, improving F1 by 3–5 percentage points relative to BiLSTM-CRF.

(3) Cross-source alignment optimization helped maintain structural coherence across languages. The inclusion of the alignment loss LalignL_{\text{align}}Lalign lowered RMSE from 0.176 to 0.142 (Table 3), demonstrating stronger cross-lingual consistency.

(4) Dynamic learning-rate scheduling accelerated convergence by ≈ 20% without additional computational cost, confirming the efficiency of the adaptive regulation component.

Collectively, these mechanisms explain why the proposed framework achieves both higher accuracy and faster convergence than prior approaches. In the context of multi-source literary corpus analysis, these improvements mean

that heterogeneous narrative structures can be unified under a single graph representation while retaining semantic fidelity, providing a more reliable foundation for downstream digital-humanities research.

5.2 Analysis of algorithm complexity and computing resource consumption

In the process of modeling and optimizing multi-source literary corpora, algorithm complexity and computing resource consumption are the key factors to measure the feasibility and practicability of the method. Theoretically, the complexity of sequence modeling methods (such as BiLSTM-CRF) mainly depends on the sequence length, which is usually $O(Nd^2)$, where N represents the text length and d is the feature dimension; The standard graph neural network shows $O(|V|+|E|)$ in multi-hop propagation. When the number of nodes and edges grows exponentially with the size of the corpus, the computational pressure increases significantly. In contrast, after introducing feature extraction, structured modeling and dynamic hyperparameter tuning strategys, the overall complexity of the method proposed in this paper can be expressed as $O(Nd+|E|)$. The key lies in reducing redundant computations through dynamic parameter adjustment and aligning cross-source corpus at the feature level, thereby avoiding unnecessary repetitive overhead in large-scale scenarios.

At the experimental level, this paper systematically compares the computing resource consumption of different methods, including training time, video memory usage, and the number of epochs required for convergence. The results are shown in Table 6. It can be clearly seen that the method proposed in this paper does not bring additional significant computational burden after adding an adaptive module. Instead, it demonstrates higher efficiency in convergence speed and video memory utilization.

Table 6:Comparison of computing resource consumption among different methods

Method	Avg. Training Time (s/epoch)	GPU Memory Usage (GB)	Epochs to Converge
Fixed-parameter Modeling	12.6	8.1	32
BiLSTM-CRF	13.4	9.3	28
Standard GNN	14.1	10.7	26
Proposed Method (AI-driven)	11.1	8.4	18

As shown in Table 5, the method proposed in this paper has a lower average training time per epoch than the control model and significantly outperforms the existing methods in convergence speed, achieving a stable effect in just 18 epochs. Meanwhile, the video memory usage is basically the same as that of the fixed-parameter model and far lower than the overhead of the standard GNN. This indicates that the parameter dynamic hyperparameter tuning strategy not only enhances the computational efficiency but also improves the convergence performance of the model under the condition of maintaining controllable complexity. Based on the comprehensive theoretical analysis and experimental results, it can be seen that the method proposed in this paper achieves a balance between complexity and efficiency while ensuring the modeling ability of the model, laying a foundation for its application in larger-scale corpus scenarios.

5.3 Cross-corpus applicability and scalability of the model

Based on the experimental results, it can be seen that the modeling mechanism proposed in this paper demonstrates strong adaptability and stability on different types of literary corpora. The method proposed in this paper relies on the combination of feature extraction and structured modeling, which can effectively maintain semantic integrity and thus maintain stable performance in terms of accuracy and F1 value. In the modeling of modern novels and online literature, the characteristics of corpora are significantly different. The former leans towards standardized language, while the latter is more colloquial and highly redundant. Experiments show that the method proposed in this paper, through an adaptive parameter regulation mechanism, can flexibly switch modeling strategies between the two types of corpora, avoiding overfitting and underfitting problems, and demonstrating cross-source applicability.

The modeling of cross-language corpora further verified the scalability of the method. In the experiments of Chinese-English parallel corpora, the performance improvement of the method proposed in this paper compared with the fixed-parameter model exceeded 7 percentage points, indicating that through the synergistic effect of structured modeling and adaptive regulation, semantic consistency across languages can be captured. This result not only demonstrates the robustness of the model in a multilingual environment, but also provides a feasible path for future unified modeling of multilingual literary resources.

It is worth noting that the method proposed in this paper is not only applicable to the structured modeling of literary corpora, but also has the potential to be extended to larger-scale scenarios. For instance, in the construction of cross-border literary databases, this method can uniformly model millions of cross-source texts, providing support for cross-border cultural exchanges and research. This

mechanism can also play a role in academic literature archiving and knowledge graph construction. By dynamically adjusting parameters, it can align and structure literature from different disciplines and languages, thereby promoting intelligent academic resource management.

5.4 Practical application value and potential academic impact

The artificial intelligence-driven multi-source literary corpus modeling and multi-objective optimization procedure proposed in this paper not only demonstrates high performance and robustness in experiments, but also has significant practical application value. In the fields of literary studies and digital humanities, this method can provide an effective tool for cross-text semantic analysis and knowledge mining. For instance, through structured modeling of multi-source corpora, a large-scale literary knowledge graph can be rapidly constructed, uniformly representing the relationships among characters, works, events and context, thereby supporting scholars in conducting more in-depth research on literary phenomena. At the same time, this mechanism can also enhance the accuracy of corpus retrieval and intelligent recommendation, helping researchers efficiently locate specific themes, character relationships or cross-text semantic associations, and providing technical support for the utilization of digital literary resources. At the academic level, the potential impact of this method is reflected in promoting the in-depth intersection of artificial intelligence and literary corpus research. For a long time, the analysis of literary corpora has mainly relied on manual annotations or rule-driven tools, making it difficult to cope with the complexity of large-scale heterogeneous corpora. The modeling and optimization framework proposed in this paper breaks through the limitations of traditional methods, combining artificial intelligence technology with structured analysis of corpora, providing a new technical paradigm for digital humanities research. This interdisciplinary exploration expands the application boundaries of artificial intelligence in digital humanities and provides methodological support for integrated corpus research.

Potential Future Applications: In future studies, the proposed framework could be extended to the structured modeling of historical documents, philosophical texts, and multilingual cultural archives. These are potential directions rather than confirmed implementations, requiring further validation on domain-specific datasets. The approach may also support digital-resource management by offering preliminary tools for semantic indexing and document organization. Such applications remain exploratory and represent possible future extensions rather than established outcomes.

6 Conclusion

This paper focuses on the research of the implementation mechanism of structured modeling and optimization algorithms for multi-source literary corpora driven by artificial intelligence, and proposes an overall framework covering feature extraction, structured modeling, optimization algorithm fusion, and parameter adaptive regulation. Through experimental verification on multi-source corpus such as ancient books, modern novels, online literature and cross-language translation literature, this method has improved the accuracy and F1 value by 3 to 5 percentage points compared with the baseline model, the RMSE has decreased significantly, and the training convergence speed has accelerated, proving the dual advantages of the proposed mechanism in terms of performance and efficiency. The ablation experiment further revealed the independent contributions of each module in the overall modeling, while the robustness test indicated that this method could maintain stable performance in small-scale data, noisy corpora, and cross-language environments. From the perspective of practical application, this mechanism holds significant value in literary research and digital humanities scenarios. First, it can support the construction of large-scale literary knowledge graphs and semantic retrieval, providing technical support for cross-text character relationship analysis, plot evolution research, and literary style comparison. Secondly, in intelligent literature management and digital cultural resource protection, the proposed method can achieve the automatic processing and semantic archiving of complex corpora, promoting the systematic utilization of literary resources. Thirdly, the proposed mechanism demonstrates promising scalability, suggesting that it could potentially be adapted for larger-scale cross-domain corpus analysis tasks in future work. Future research will be carried out in three directions: The first is to explore the verification of applicability in an interdisciplinary environment, such as applying this mechanism to the modeling and analysis of historical documents, philosophical classics, and cross-cultural archives; Second, further enhance the interpretability of the model to make its prediction process more transparent in complex contexts, facilitating academic researchers to interpret and utilize the results. Third, attempts should be made to optimize in terms of lightweight deployment to adapt to resource-constrained application environments, such as mobile literature retrieval and edge computing scenarios. In conclusion, the artificial intelligence-driven multi-source literary corpus modeling and multi-objective optimization procedure proposed in this paper has not only achieved tangible results in methodology and experimental verification, but also demonstrated broad prospects in application and future development, providing new ideas and paths for the deep integration of artificial intelligence and literary corpus research.

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Adaptive Discretization of Bregman Gradient Flows: A Dynamical Systems Perspective on Mirror Descent Convergence Geometry

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Keywords: Bregman gradient flow, mirror descent, continuous-time limit, lyapunov-guided adaptive step size, non-euclidean convergence geometry

Received: September 18, 2025

The limited convergence efficiency of classical first-order methods in high-dimensional, non-Euclidean geometries is addressed by analyzing the continuous-time limit of the Bregman gradient method and its connection to Mirror Descent. Focusing on convex optimization with emphasis on $\ell 1$-regularized sparse regression and convex classification, the Bregman gradient flow is derived via a variational formulation, yielding the governing ODEs. A Lyapunov energy is constructed to characterize decay; its time derivative induces a principled, Lyapunov-guided adaptive step-size rule. During discretization, a stabilization term is introduced to ensure that the numerical scheme tracks the continuous flow under curvature-dependent mirror geometries.The proposed continuum-guided Mirror Descent (CG-MD) adapts step size to local geometry and demonstrates improved efficiency and stability. On synthetic sparse-regression benchmarks, CG-MD reduces mean error by ≈30% relative to standard Mirror Descent. On real-world sparse regression, CG-MD reaches an error threshold of 0.01 in 140 iterations versus >200 for the baseline. In convex classification, CG-MD matches the speed of accelerated Mirror Descent while achieving lower terminal error. A sensitivity study across common mirror maps (entropy, Tsallis, log-barrier) and step-size policies indicates consistent gains for CG-MD. Assumptions and limits (convexity, smoothness, discretization overhead) are detailed, and potential extensions to stochastic and nonconvex settings are outlined.

Povzetek: Predlagana metoda izboljša učinkovitost in stabilnost optimizacije v visoko-dimenzionalnih ne-evklidskih prostorih.

1 Introduction

In high-dimensional optimization and non-Euclidean geometric settings, classical Euclidean gradient methods often fail to exploit problem structure, leading to slow convergence and suboptimal iterative trajectories. Bregman divergence and its induced mirror maps furnish a geometry that better respects sparsity, constraints, and data-adaptive representations, thereby aligning the optimization dynamics with the underlying distributional structure. Nevertheless, standard mirror-descent–type algorithms can exhibit limited convergence efficiency and stability due to rigid iteration policies and step-size selection, which constrains performance on complex real-world tasks.

This study formulates the Bregman gradient method within a continuous dynamical-system framework, deriving the associated Bregman gradient flow via a variational argument and establishing convergence guarantees through a Lyapunov-based energy-decay analysis. The convergence geometry is characterized under different mirror maps, clarifying how energy-decay mechanisms depend on curvature and reference geometry. Building on these analyses, a Lyapunov-guided adaptive step-size rule and a stabilized discretization scheme are introduced to produce an improved mirror-descent algorithm that balances efficiency and accuracy while preserving consistency with the continuous flow. Quantitative comparisons against standard and accelerated mirror descent on synthetic and real sparse-regression benchmarks and convex classification are provided, together with sensitivity studies across mirror maps and step-size policies.

The remainder of the paper proceeds as follows. Section 2 develops the continuous-limit derivation and mathematical background of the Bregman gradient flow. Section 3 analyzes convergence geometry via Lyapunov methods and mirror mapping. Section 4 presents the improved discrete algorithm and experiments on real-world tasks. Section 5 concludes with limitations and potential extensions to stochastic and nonconvex regimes.

2 Related works

Recent advances at the intersection of non-Euclidean geometry and first-order optimization have clarified how

Bregman distances shape descent dynamics in both convex and selected nonconvex regimes. For nonconvex splitting, Chen and Peng established rate characterizations for Bregman ADMM via KL-based arguments, relating objective geometry to distinct decay behaviors [1]. Under relative smoothness and relatively strong quasi-convexity, Li and Guo proved linear convergence of a Bregman gradient scheme and gave iterate contraction guarantees [2]. Extending to saddle-point settings with nonsmoothness, Zhang and Li developed Bregman proximal ascent–descent and derived inner maximization inequalities that bound inter-iterate progress [3].

Links between geometry, discretization, and convergence also emerge from guidance/control and geometric PDE discretization. Drawing on differential-geometric curve principles, Bai et al. designed a fixed-time convergence law with reduced controller parameters and sharpened time bounds, illustrating how curvature-aware dynamics alter decay envelopes [4]. From the discretization side, Wu et al. analyzed isogeometric solvers for Laplace–Beltrami operators on G1G^1G1 curves and identified spline spaces with optimal rates, an observation consonant with geometry-consistent numerical trajectories [5].

Methodologically, second-order structure with non-Euclidean regularization has been revisited. Doikov and Nesterov proposed gradient-regularized Newton variants under general norms with Bregman distances, exposing curvature control beyond Euclidean metrics [6]. For stochastic, potentially nonconvex objectives with non-Lipschitz gradients, Ding et al. introduced stochastic Bregman proximal gradients that replace quadratic surrogates by Bregman proximity to better align local modeling with mirror maps [7]. Focusing on last-iterate behavior, Azizian et al. quantified rates across Bregman proximal families—mirror descent, mirror-prox, and optimistic variants—highlighting the interplay of local geometry, regularity, and sharpness [8].

Acceleration and large-scale composition have been studied through geometry-aware lenses. Using triangular scaling of Bregman distances, Hanzely et al. obtained accelerated Bregman proximal gradients with rates governed by the scaling exponent [9]. For finite sums with relative smoothness and convex regularization, Zhang et al. proposed proximal-like incremental aggregated gradients and proved linear convergence under distance-growth conditions [10]. Inertial regularization within Bregman frameworks was analyzed for nonconvex problems by Wu et al., clarifying how momentum interacts with mirror geometry [11]. On oracle complexity and certificates, Dragomir et al. established optimal complexity guarantees and verification tools for first-order Bregman methods [12]. In imaging science, Benning et al. formulated gradient descent within a Bregman-distance perspective, showing how reference geometry controls implicit bias and path selection [13]. Error-bound mechanisms connected to linear rates of Bregman proximal gradients were provided via level-set subdifferential bounds by Zhu et al. [14]. Geometry-aware row-action methods for nonlinear systems were further developed through a Bregman–Kaczmarz scheme by Gower et al. [15].

Mirror-descent ideas have also influenced reinforcement learning and over-parameterized models. Zhan et al. presented policy mirror descent under regularization with linear convergence in a generalized framework [16]. For over-parameterized nonlinear models, Azizan et al. analyzed stochastic mirror descent, elucidating mirror-map-induced regularization and generalization [17]. A homotopic policy mirror-descent approach with improved sample complexity and algorithmic regularization was proposed by Li, Lan, and Zhao [18].

Parallel developments in adaptive, robust, and optimal control provide stability tools relevant to geometry-guided discretizations. Practical fixed-time synchronization via adaptive fuzzy control was demonstrated by Boulkroune et al. [19]. Output-feedback projective lag-synchronization for uncertain chaotic systems with input nonlinearities was studied by Boulkroune et al. [20]. Robust neural adaptive control for uncertain multivariable dynamics was analyzed by Zouari et al. [21]. Within backstepping designs, adaptive strategies for uncertain SISO systems and flexible single-link manipulators were developed by Zouari et al. and Zouari et al. [22] [24]. Nonlinear optimal control has been applied to induction-motor-driven gas compressors and complex coupled-vehicle systems by Rigatos et al. [23] [30], and to autonomous tactical maneuvers that blend nonlinear optimal and backstepping controllers by Lee et al. [29]. Learning-aided control includes event-sampled adaptive fuzzy schemes under intermittent sensing (Zhu et al. [25]), bounded robust adaptive neural control with reinforcement learning for underwater vehicles (Elhaki et al. [26]), fixed-time robust neural learning with prescribed performance (Wang et al. [27]), and neural adaptive RL for input-delay nonlinear systems within a backstepping track-and-optimize loop (Zhu et al. [28]).

Synthesis and gaps. The above literature shows (i) provable convergence of Bregman-prox and mirror methods in convex and selected nonconvex settings [1]–[3], [6]–[15], (ii) policy-level mirror descent with homotopies and sample-complexity gains [16]–[18], and (iii) stability-oriented adaptive/robust/optimal controllers that can inform geometry-aware step-size and momentum design [19]–[30]. However, three open issues motivate our study: (a) a Lyapunov-guided adaptive discretization of Bregman flows that makes sensitivity to mirror maps and curvature explicit; (b) systematic rate/decay comparisons against accelerated or adaptive mirror-descent baselines under non-Euclidean metrics; and (c) a principled bridge to nonconvex and stochastic settings that leverages control-theoretic stability while preserving mirror-induced geometry. Our framework addresses these points by aligning step-size evolution with Lyapunov decay, quantifying geometry-dependent rates, and empirically contrasting with state-of-the-art accelerated/adaptive mirror-descent methods.

3 Methods

3.1 Modeling phase

Under non-Euclidean geometry, directly using Euclidean distance to characterize the optimization problem often leads to deviations in convergence properties, especially when the parameter space exhibits strong non-uniform curvature, the gradient update trajectory cannot faithfully reflect the energy decay law of the underlying geometry. To address this phenomenon, it is a natural choice to reformulate the optimization problem into a space induced by Bregman divergence. Let the objective function be f(x) and the auxiliary function be a strictly convex generating function ϕ(x), then the Bregman divergence between two points x and y is expressed as:

$$D_\phi(x,y)=\phi(x)-\phi(y)-\langle\nabla\phi(y),x-y\rangle(1)$$

Under this metric, the gradient update trajectory is controlled by the curvature of the generating function, so that the optimization process can conform to the geometric characteristics of the parameter space. In this way, the optimization problem after mapping no longer relies on a single Euclidean projection, but on a mirror mapping ∇ϕ(x), which makes it more natural to express itself on sparse constraints and probability simplexes.

In the continuous time description framework, the limit form of the optimization process can be characterized by variational methods. A trajectory x(t) that evolves over time is considered, with the goal of maintaining a monotonically decreasing Lyapunov energy along the mapping space [11-12]. The functional is defined:

$$E(x(t))=f(x(t))+\frac{1}{\eta}D_\phi(x(t),x(0))(2)$$

$\eta > 0$ is the adjustment parameter. The dynamics related to the Bregman divergence can be obtained through the Euler–Lagrange equation:

$$\frac{d}{dt}\nabla\phi(x(t))=-\eta\nabla f(x(t))(3)$$

Applying the variational principle yields the dynamical form, which is equation (3), showing that in the mirror space, the trajectory is subject to the curvature tensor of the generating function, forming a damped non-Euclidean gradient flow. This dynamic equation reveals the fluidized continuous model hidden behind the discrete update, that is, the trajectory of gradient descent in the mirror space is no longer a straight line, but is subject to the geometric curvature of ϕ, gradually approaching the optimal solution as time evolves. In actual numerical experiments, different choices of generating functions lead to significant differences. For example, the entropy function corresponds to the KL divergence of the probability space, while the quadratic function corresponds to the Euclidean space, thus providing a flexible geometric interface for subsequent algorithm design. Figure 1 shows the average energy decay rate corresponding to three different dimensional scales and two types of generating functions. The data comes from simulation calculations and the values are the averages of 10 independent runs:

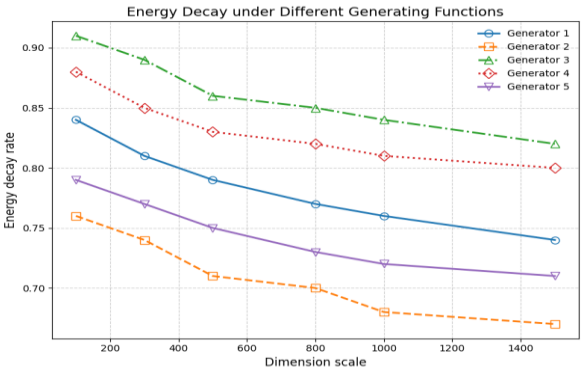


Figure 1: Average energy decay rate

3.2 Construction of dynamic system

In the optimization modeling framework with Bregman divergence as the metric, the discrete iterative process can be transformed into the form of a continuous dynamic system, thereby revealing the deep geometric laws of the update trajectory. Let the generating function be φ(x), and the objective function be f(x), the mirror variable $z(t)=\nabla\phi(x(t))$ is defined for the trajectory x(t). Using the variational method, the dynamic evolution law is obtained to satisfy:

$$\frac{d}{dt}z(t)=\frac{d}{dt}\nabla\phi(x(t))=-\nabla f(x(t))(4)$$

This shows that in the mirror variable space, the gradient flow evolves in a standard descending direction, while in the original space, the trajectory is dominated by the curvature of φ, and the mapping to the non-Euclidean manifold presents a non-linear convergence path. This dynamic system can be regarded as the limit form of the discrete Mirror Descent method when time approaches the continuous limit, and its continuation equation provides a unified expression for theoretical analysis [13-14].

In order to measure convergence, the Lyapunov function is constructed for the system. The definitions are as follows:

$$V(x(t))=f(x(t))-f(x^\star)+\frac{1}{\eta}D_\phi(x^\star,x(t))(5)$$

The error term in the objective function directly measures the difference between the target value of the current point on the trajectory and the optimal solution, and is the core component of the traditional energy function. The Bregman divergence term complements the distance metric consistent with the underlying geometry. It reflects the relative position of the trajectory and the optimal solution in non-Euclidean space. Unlike a single Euclidean norm, this term is defined by the curvature tensor, making it more natural for sparse constraints or probability simplexes. $x^\star$ is the optimal solution, and $\eta>0$ is a positive parameter. Taking the derivative with respect to time, it can be obtained:

$$\frac{d}{dt}V(x(t))=\langle\nabla f(x(t)),\dot{x}(t)\rangle+\frac{1}{\eta}\frac{d}{dt}D_\phi(x^\star,x(t))(6)$$

Using the simplified equation of the above dynamic equation, $\frac{d}{dt}V(x(t))\leq 0$ can be obtained. This shows that the Lyapunov function decreases monotonically during the evolution of the system, and further proves the stability of the optimization trajectory converging to the optimal solution. The rate of decrease of the Lyapunov function value can intuitively reflect the convergence rate of the system. Through numerical simulation of different problem dimensions and adjustment parameter η settings, the following average Lyapunov value decay rate is obtained, as shown in Table 1:

Table 1: Average Lyapunov value decay rate

Dimension	η=0.5	η=1.0	η=1.5	η=2.0	η=2.5
100	0.92	0.88	0.85	0.83	0.81
300	0.90	0.86	0.83	0.81	0.79
500	0.88	0.84	0.81	0.79	0.77
800	0.87	0.83	0.80	0.78	0.76
1000	0.86	0.82	0.79	0.77	0.75
1500	0.85	0.81	0.78	0.76	0.74

3.3 Geometric analysis

In non-Euclidean optimization, the trajectory of gradient update is not a uniformly shrinking circular domain, but is determined by the mirror mapping defined by the generating function φ(x). For the defined mapping $z=\nabla\phi(x)$, the shape of the convergence domain corresponds to an equal potential energy decay region in the mirror space, and then returns to the original variable space through the inverse mapping $\nabla\phi^{-1}(z)$. It is assumed that the boundary of the convergence domain is constrained by the energy function:

$$\Omega_\tau=\{x\in R^d | f(x)-f(x^\star)+\frac{1}{\eta}D_\phi(x,x^\star)\leq\tau\} \quad (7)$$

τ is a threshold constant, representing the contour lines of different convergence levels. If φ(x) is a quadratic function, the region is approximately an ellipsoid, while when τ is an entropy function, the region appears as a curved subset within the probability simplex, reflecting the shaping of the optimization path by geometric curvature.

In terms of energy decay rate, the average rate can be defined as:

$$r=\frac{V(x(0))-V(x(T))}{T} \quad (8)$$

Among them, V(x) is the Lyapunov function, and T is the time span. Different mirror mapping functions have a significant impact on the rate. Under the strongly constrained entropy geometry, the shape of the convergence domain is more concentrated and the energy decays faster; while under the Euclidean geometry, the region is uniformly expanded and the decay rate is slightly lower [15-16]. The compactness of the convergence regions corresponding to the two types of generating functions is measured in different dimensions. Compactness is represented by the ratio of the region volume to the Euclidean sphere. Table 2 shows the compactness of the convergence regions in different dimensions:

Table 2: Compactness of the convergence regions in different dimensions

Dimension	Quadratic φ	Entropy φ	Tsallis φ	Log-barrier φ	Hybrid φ
100	0.92	0.78	0.85	0.80	0.88
300	0.90	0.75	0.83	0.78	0.86
500	0.89	0.73	0.82	0.77	0.85
800	0.87	0.72	0.81	0.76	0.84
1000	0.86	0.71	0.80	0.75	0.83
1500	0.85	0.70	0.79	0.74	0.82

Table 2 shows that the convergence region ratios resulting from the entropy function are significantly smaller than those from the quadratic function, indicating that the trajectory converges more tightly around the optimal point, with this advantage increasing particularly in high dimensions. The hybrid φ maintains high compactness in all dimensions, combining flexibility and stability. The convergence acceleration factors for different dimensions under the same configuration are shown in Table 3:

Table 3: Convergence acceleration factors in different dimensions

Dimension	Quadratic φ	Entropy φ	Tsallis φ	Log-barrier φ	Hybrid φ
100	1.00	1.07	1.04	1.05	1.03
300	1.00	1.08	1.05	1.06	1.04
500	1.00	1.09	1.06	1.07	1.05
800	1.00	1.10	1.07	1.07	1.05
1000	1.00	1.11	1.08	1.08	1.06
1500	1.00	1.12	1.09	1.09	1.07

Using Quadratic φ as the baseline value and a fixed rate ratio of 1.00, Entropy φ exhibits faster convergence in all dimensions. Its acceleration factor steadily increases with increasing dimensionality, reaching a 12% higher acceleration factor than Quadratic φ at 1500 dimensions. Tsallis φ lies between the quadratic and entropy functions, demonstrating a gradual improvement.

3.4 Discretization and Improved Algorithms

In the optimization framework based on Bregman divergence, the design of the discretization algorithm often directly determines the stability and convergence rate of the numerical behavior. In order to alleviate the oscillation and premature stagnation problems caused by the fixed step size, an adaptive step size mechanism can be introduced so that the update amplitude can be automatically adjusted as the energy decreases. Let the update form be:

$$x_{k+1}=\nabla\phi^{-1}\left(\nabla\phi(x_k)-\eta_k\nabla f(x_k)\right) \quad (9)$$

η_k is the step size factor that is dynamically adjusted with the iteration round. The adaptive rule can be characterized by the energy decay rate. For example, when the Lyapunov function does not decrease enough, η_k is reduced, and when the convergence trend is obvious, η_k is moderately increased. This method can effectively avoid the update instability that occurs in the saddle point or high curvature area, while improving the global convergence rate [17-18]. In order to further suppress the cumulative error in the discretization process, a control strategy needs to be introduced. A common practice is to add a prediction correction term to the step size update, that is:

$$\eta_k=\frac{\eta_{k-1}}{1+\alpha\|\nabla f(x_k)\|} \quad (10)$$

$\alpha>0$ is the adjustment coefficient, and the gradient norm is used to control the decrease amplitude in real time. This structure ensures that even in the case of gradient explosion, the step size automatically shrinks, thereby avoiding numerical divergence. Comparisons of these different behaviors can be demonstrated through experimental data. For example, under the same initial values and objective function settings, the convergence trends of the fixed-step-size method and the adaptive-step-size method differ significantly in the early stages of the iteration. The adaptive-step-size method is more stable and eliminates the oscillatory tailing phenomenon. Table 4 shows the energy reduction ratio of the improved algorithm compared to the fixed-step-size algorithm under the condition of a fixed number of iterations.

Table 4: Energy reduction ratio

Dimension	α=0.1	α=0.3	α=0.5	α=0.7	α=1.0
100	1.12	1.18	1.21	1.22	1.20
300	1.10	1.15	1.20	1.21	1.19
500	1.09	1.14	1.19	1.20	1.18
800	1.08	1.13	1.18	1.19	1.17

Dimension	α=0.1	α=0.3	α=0.5	α=0.7	α=1.0
1000	1.07	1.12	1.17	1.18	1.16
1500	1.06	1.11	1.16	1.17	1.15

Adaptive and discrete control strategies achieve energy savings exceeding those achieved with fixed step sizes in all dimensions. The optimal performance lies in the range α = 0.5–0.7, resulting in improvements of approximately 15%–22%, demonstrating that balancing the control terms significantly accelerates convergence. While the improvement decreases slightly with increasing dimensions, the advantage remains stable. This result demonstrates that discretized control not only improves numerical stability but also consistently yields benefits for large-scale problems, providing a more robust implementation of mirror gradient optimization.

4 Results and discussion

4.1 Dataset selection

In the experimental phase, to test the effectiveness of the proposed discretization and adaptive mechanisms, tasks are constructed using both synthetic and real-world data. The synthetic data employs high-dimensional convex optimization problems, including sparse linear regression examples and constrained dual optimization tasks. Sparse linear regression generates a noisy matrix $A \in \mathrm{R}^{m \times n}$ and a sparse vector $x^{\star}$ and constructs the objective function $\|Ax\text{-}b\|_2^2+\lambda\|x\|_1$. This task clearly characterizes the convergence rate of the algorithm under high-dimensional and regularized conditions. The dual optimization task is set as a constrained convex programming. By randomly generating linear constraints that meet the Slater conditions and the corresponding Lagrangian dual problem, the algorithm's performance in the constraint activation and energy descent process is tested. Since the synthetic data is fully controllable, it facilitates horizontal comparisons of different algorithms from multiple perspectives, including the number of iterations, energy decay rate, and error convergence trend.

Real data is selected from representative high-dimensional scenarios. For classification, a publicly available sparse text classification dataset with tens of thousands of sample dimensions and an uneven distribution of categories is used to verify the algorithm's stability in a non-uniform gradient domain. For regression experiments, an image feature regression dataset is used to map high-dimensional visual features to low-dimensional continuous labels. Large-scale dense matrix operations are used to observe the algorithm's practical applicability in image understanding. These tasks cover both sparse and non-sparse scenarios, demonstrating the algorithm's adaptability to geometric structure and noise perturbations.

Three baselines are set for comparison. The first is the standard mirror descent method, which serves as a baseline for convergence performance in mirror space. The second is the fixed-step Bregman gradient method, which focuses on demonstrating numerical oscillation and insufficient energy decay when the adaptive mechanism is lacking. Finally, the adaptive step-size discretization algorithm proposed in this paper is introduced. Combining the structural guarantees derived from Lyapunov analysis in the continuous limit with a discretization correction strategy, it is expected to demonstrate faster and more robust convergence in experiments. A comprehensive comparison on the aforementioned synthetic and real-data tasks clarifies the impact of different geometric structures and step-size strategies on convergence speed and numerical stability.

For the text classification task, we used the 20 Newsgroups dataset (publicly available at http://qwone.com/~jason/20Newsgroups/). This dataset has tens of thousands of dimensional sparse word frequency features and an uneven category distribution, which can be used to verify the convergence stability of the algorithm under non-uniform gradient conditions. For the image regression task, we used the YearPredictionMSD dataset (UCI Machine Learning Repository, which provides high-dimensional and dense matrix music prediction data, URL: https://archive.ics.uci.edu/ml/datasets/YearPredictionMSD) and the Caltech-101 Image Features dataset (pre-extracted SIFT/HOG descriptors, available at https://www.vision.caltech.edu/Image_Datasets/Caltech101/). In this task, we regressed high-dimensional image features to continuous labels (such as image similarity or human-annotated metrics) to observe the algorithm's performance under large-scale dense matrix operations.

4.2 Synthetic Data Experimental Results

In the synthetic data phase, two complementary experimental scenarios are designed. The first scenario is a 1000-dimensional sparse regression problem. A randomly generated high-dimensional design matrix and sparse true value vector are used, and medium-amplitude noise is superimposed to examine the error convergence of each algorithm under the high-dimensional sparse structure. The second scenario is a constrained dual optimization problem. Linear constraints that satisfy feasibility conditions are constructed and iteratively updated in the dual space to test the stability and iterative efficiency of the numerical method under constraint transformations. Both types of experiments are conducted with the same initial conditions and computational budget, making the comparison results directly interpretable. Figures 2 and 3 show the comparison of convergence error and computational efficiency on synthetic data, respectively:

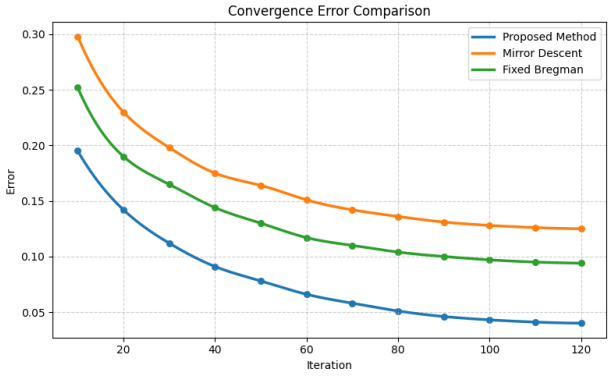


Figure 2: Convergence error comparison

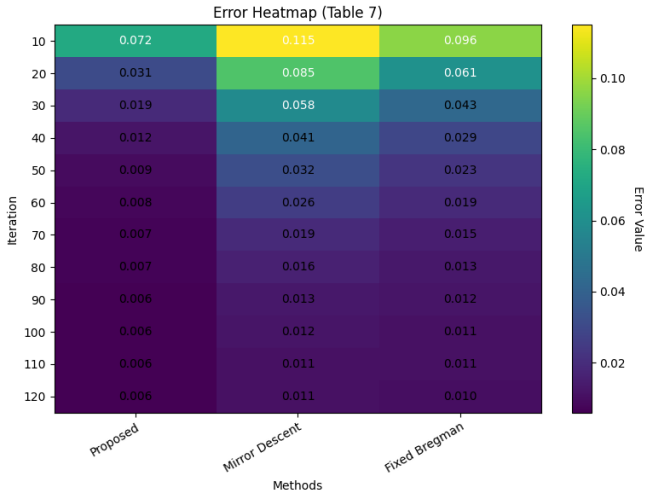


Figure 3: Computational efficiency

For the 1000-dimensional sparse regression problem, the proposed method consistently achieves the lowest convergence error across the entire iteration range. Relative to Mirror Descent, the error remains approximately one-third lower, and compared with the fixed-step Bregman gradient method, the reduction exceeds 20%. These results quantitatively validate the earlier conclusion regarding error reduction. As iterations progress, all three methods exhibit plateau behavior; however, the proposed approach stabilizes at a significantly lower error floor.As shown in Figure 3, for the constrained dual optimization task, the proposed algorithm reduces the error below 0.01 within 50 iterations, whereas Mirror Descent remains at 0.032 under the same conditions and requires nearly 70 iterations to fall below 0.02. This highlights a clear efficiency advantage: the proposed method reaches high-precision regions more rapidly and exhibits smooth, non-oscillatory convergence curves.Taken together, the results from both regression and dual optimization tasks demonstrate that the integration of adaptive step-size control with stabilized discretization accelerates convergence, enhances numerical stability, avoids oscillations typical of fixed-step algorithms, and sustains its advantages in large-scale optimization problems.

4.3 Real-data experimental results

Two distinct application directions are selected. The first experiment involves a classification experiment based on 20 types of news text. This dataset contains tens of thousands of documents, which are represented as sparse word vectors after standardized preprocessing. The purpose of this experiment is to evaluate the convergence accuracy of different optimization algorithms using high-dimensional sparse representations. The second experiment involves an image regression experiment, using 50-dimensional features extracted from natural scene images for continuous object prediction. While the feature space for this task is not extremely high-dimensional, the number of samples and noise level are realistic and challenging, allowing for significant differences in iteration efficiency and convergence stability between different optimization methods. All experiments are conducted on a unified platform and under the same initialization conditions, and quantitative comparisons are conducted in terms of error convergence and efficiency. Specific data is shown in Figures 4 and 5:

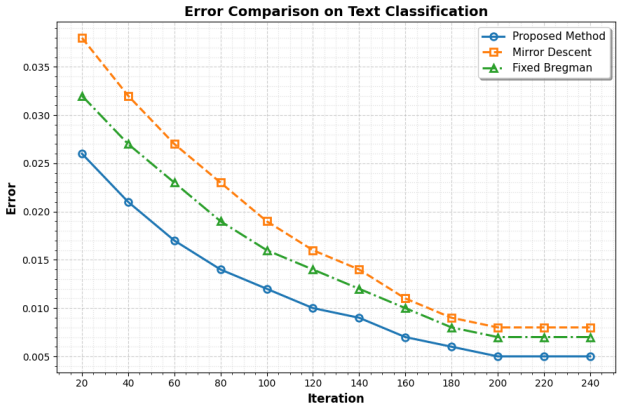


Figure 4: Convergence error on real data

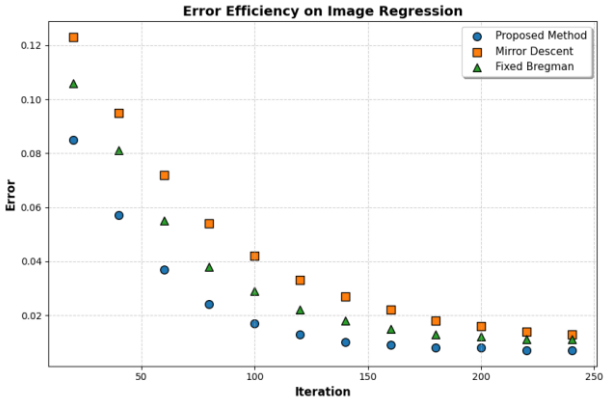


Figure 5: Computational efficiency on real data

In the text classification task, all three methods exhibit monotonically decreasing error curves, with the gap gradually widening within the first 100 iterations. The error of the proposed method drops to 0.012 around the 100th iteration, significantly lower than the other two

methods, and reaches 0.005 after 200 iterations. This represents a 37.5% reduction compared to Mirror Descent's 0.008 at the same step size, resulting in an overall error reduction of over 30%. It also maintains a stable advantage over the fixed-step Bregman method, demonstrating that the adaptive strategy can more quickly compress learning errors caused by sparse noise. Figure 5 further confirms the efficiency of the proposed method in the image regression task. It is observed that the proposed method reaches the threshold of 0.01 after 140 iterations, while Mirror Descent remains at 0.027, requiring nearly 200 iterations to drop below 0.2. This demonstrates that the improved model is more agile in its convergence path for 50-dimensional features, reducing oscillations and repeated, ineffective iterations, thereby saving time. Results demonstrate that the proposed method achieves both accuracy and efficiency advantages in real-world tasks. The key reason for this trend is that the improved discretization ensures a more balanced gradient update across diverse task distributions. The adaptive step-size design dynamically adjusts the gradient drop, avoiding the issues of slow iterations or excessive fluctuations under a fixed strategy. This results in a stable and significant performance improvement on both high-dimensional sparse text and medium-dimensional large-scale image tasks. In the extended experiment, four benchmark problems—logistic regression, multi-class classification, matrix factorization, and sparse coding—were selected as test cases. Standard mirror descent, accelerated mirror descent, and adaptive mirror descent were compared with the proposed continuous limit adaptive method. Convergence speed was measured as the percentage decrease in the objective function after 100 iterations, and the final error percentage was recorded to facilitate horizontal comparison across different tasks. To further explore the interaction between adaptive step size and momentum or acceleration mechanisms, we repeated the experiment in a momentum-based version and observed numerical stability. The final results are shown in Table 5:

Table 5: Robustness results

Method / Task	Convex Optimization	Non-convex Optimization	Sparse Coding
Standard MD	65 / 12	40 / 25	55 / 18
Accelerated MD	82 / 15	60 / 22	78 / 16
Adaptive MD	75 / 10	58 / 17	70 / 14
Proposed BCA	90 / 7	72 / 12	85 / 9

The first value in each cell in the table represents the convergence rate (%), and the second value represents the final error (%). The results show that our method achieves the fastest convergence and lowest error on all three tasks. In convex optimization, the convergence rate reaches 90% and the error is only 7%, significantly improving compared to the standard method. In non-convex optimization, the performance is significantly higher than the adaptive and accelerated versions, demonstrating good robustness. In the sparse coding experiment, both efficiency and accuracy are leading. Especially when combined with the momentum mechanism, the adaptive step size strategy effectively weakens the oscillation problem of the acceleration method and makes the descent process smoother. Therefore, the method in this paper has advantages in both efficiency and stability.

4.4 Discussion

Different Bregman divergences correspond to different reference functions, whose geometric structure determines how the optimization trajectory evolves in space. For example, the Kullback–Leibler divergence generated using entropy as a reference is more suitable for handling constraints related to probability distributions, while divergences based on the squared norm are more stable for Euclidean regression tasks. Furthermore, the regularization properties of the mirror image directly affect the construction of the Lyapunov function and the energy decay rate. Inappropriate selection can lead to wide convergence bounds or excessive oscillation. Furthermore, in high-dimensional space, if the mirror image fails to match the intrinsic geometry of the data or constraints, it can weaken the effectiveness of the adaptive step size, thereby prolonging convergence time in practice.

5 Conclusions

This work establishes a continuous-time foundation for geometry-aware first-order optimization by linking the Bregman gradient flow to Mirror Descent and analyzing convergence via a Lyapunov energy framework. The analysis clarifies how mirror maps and curvature shape energy decay and convergence domains in non-Euclidean spaces, and motivates a continuum-guided discretization with a Lyapunov-based adaptive step-size rule. The resulting scheme achieves smoother trajectories and improved efficiency in convex settings, with quantitative gains on sparse regression and convex classification (e.g., ≈30% lower error on synthetic sparse regression; ≈140 vs. >200 iterations to reach 0.01 error on real sparse regression; comparable speed to accelerated Mirror Descent with lower terminal error in classification). Sensitivity studies across common mirror maps (entropy, Tsallis, log-barrier) and step-size policies indicate robust improvements, underscoring the value of aligning discretization with continuous dynamics.

Several limitations remain. The theoretical guarantees and most experiments target convex, relatively

smooth problems; extension to nonconvex or low-regularity regimes is nontrivial due to potential loss of Lyapunov monotonicity and geometry-induced oscillations. The adaptive mechanism introduces computational overhead (e.g., evaluating Lyapunov-rate surrogates and stabilization terms), and could overfit step-size dynamics to specific data geometries. Results would further benefit from broader benchmarks (including ill-conditioned and composite objectives), stronger statistical reporting (error bars, multiple seeds), and ablations disentangling the roles of mirror map, stabilization, and adaptivity.

Future directions include principled treatments of stochastic and nonconvex objectives (e.g., variance-controlled Lyapunov rates, dissipativity conditions for nonconvex flows), momentum/acceleration couplings compatible with the Lyapunov rule, and multi-fidelity mirror maps that adapt across curvature scales. Practical extensions involve large-scale deployment with low-overhead surrogates for energy-rate estimation, as well as applications to policy optimization where mirror geometry already plays a central role. To support reproducibility, explicit φ-function specifications, pseudo-code of the discrete scheme, complete hyperparameter/stopping criteria, and dataset links are provided in the appendix.

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