International Journal of Research in Advanced Engineering and Technology
www.allengineeringjournal.in
ISSN: 2455-0876
Received: 30-11-2025, Accepted: 14-01-2026, Published: 29-01-2026
Volume 12, Issue 1, 2026, Page No. 1-6

Adaptive fingerprint feature extraction using reinforcement learning-based filter selection

Dr. Sureshbabu N
Assistant Professor, Department of Computer Application, Akshaya College of Arts and Science, Coimbatore, Affiliated to Bharathiar University, Coimbatore, Tamil Nadu, India

Abstract
Fingerprint recognition systems depend on the extraction of discriminative ridge features to achieve high accuracy under diverse imaging conditions. Traditional feature extraction methods, which utilize fixed convolutional or Gabor filters, often fail to adapt to distortions, such as pressure variations, smudging, and partial prints. This study introduces a novel Adaptive Fingerprint Feature Extraction (AFFE) framework that employs a Reinforcement Learning-Based Filter Selection (RLFS) mechanism to dynamically select the optimal filter for each fingerprint region. The method integrates a Deep Q-Learning agent with a multi-scale convolutional backbone to enhance ridge clarity, maintain orientation consistency, and improve minutiae localization. Experiments conducted on the FVC2002 and FVC2004 datasets demonstrated that the proposed RLFS approach reduced the equal error rate (EER) by 13.5% and increased recognition accuracy by 8.3% compared to conventional CNN- and Gabor-based methods. The system exhibits strong robustness against noise, partial prints, and distortions, making it suitable for real-time biometric authentication.

Keywords: Fingerprint recognition, reinforcement learning, deep q-learning, feature extraction, biometric security, filter selection

Introduction
The rapid advancement of technology and increasing digitalization of services have generated significant demand for reliable and intelligent authentication systems. As security threats continue to evolve, ensuring accurate and secure identity verification has become a critical priority across a wide range of applications, including mobile banking, access control, e-governance, healthcare, and smart environments [1]. Traditional knowledge-based authentication methods, such as PIN codes, passwords, and pattern locks, remain prevalent but are highly vulnerable to common security risks, including brute-force attacks, shoulder surfing, and password leakage. Consequently, these methods often fail to provide the level of protection required for contemporary high-security systems [2].

Biometric authentication, particularly fingerprint recognition, has emerged as a compelling alternative because of the distinctiveness, universality, permanence, and ease of acquisition of fingerprints [3]. Fingerprints are extensively utilized in commercial devices, such as smartphones, laptops, and smart door locks. They are also employed in national identity programs, criminal investigations and attendance tracking systems. Despite their advantages, fingerprint-based systems are not entirely free of limitations. Variations in finger pressure, moisture, skin condition, noise, and environmental disturbances can degrade fingerprint quality and complicate recognition processes. Furthermore, biometric systems are susceptible to vulnerabilities, such as spoofing, sensor noise, and the misuse of stolen biometric templates, which can significantly impact system performance [4]. Ensuring accurate and robust fingerprint recognition under these challenging conditions remains an active research area [5].

To enhance the reliability of fingerprint recognition, researchers have increasingly adopted machine learning (ML) and deep learning (DL) methods. ML algorithms, such as support vector machines (SVM), decision trees (DT), K-nearest neighbors (KNN), and ensemble classifiers, have demonstrated strong classification capabilities in well-structured datasets [6]. Concurrently, DL-based frameworks have exhibited exceptional performance in extracting complex image patterns, rendering them ideal for tasks such as image enhancement, feature extraction and pattern recognition [7]. These models can learn hierarchical representations and capture both global and local structures within fingerprint images, resulting in significant improvements in recognition accuracy [8, 9].

Many current deep learning-based systems for fingerprint feature extraction utilize fixed convolutional filters that are uniformly applied across the image without considering local variations in quality, ridge clarity, or noise. Because fingerprint images frequently contain heterogeneous regions with varying levels of distortion, a static filter configuration may not optimally enhance all areas of an image. This results in suboptimal feature extraction and reduces the overall system accuracy. To address this limitation, adaptive and intelligent feature extraction mechanisms are required to address this limitation.

This study presents an innovative Adaptive Fingerprint Feature Extraction (AFFE) framework that employs a Reinforcement Learning-Based Filter Selection (RLFS) mechanism. In contrast to traditional systems, the proposed approach dynamically selects the most appropriate filter for each fingerprint region. A Deep Q-Learning agent assesses the local characteristics of the fingerprint and selects filters that enhance ridge clarity and reduce noise, thereby enhancing the accuracy of subsequent recognition tasks. Reinforcement learning offers robust decision-making capabilities that enable the system to continuously optimize filter selection based on feedback, rendering it highly suitable for complex real-world fingerprint variations.

Related Work

Praveen Kumar S. and Harish R [10]. proposed a multi-scale convolutional enhancement model specifically designed for noisy fingerprint images. Their methodology utilized Gabor filters with various orientations to enhance the ridge structures, followed by an estimation of the local orientation. Although this approach succeeded in improving image clarity, its effectiveness in scenarios involving high-intensity noise or irregular ridge flow patterns is constrained by its reliance on fixed Gabor parameters.

Anil R. Rao et al. [11] introduced a deep residual learning framework to enhance fingerprint images. This model employs stacked residual blocks to reconstruct intricate ridge details, while effectively suppressing noise. Although it demonstrated improved accuracy compared to traditional filters, its architecture was limited by its inability to adaptively select filters based on local ridge conditions, leading to diminished performance on partial or smudged fingerprints.

Chen et al. [12] introduced a convolutional neural network (CNN)-based system for minutiae extraction, intended to supplant traditional handcrafted techniques. This system autonomously learns ridge and valley representations from raw fingerprint images and employs heatmap regression to identify minutiae points. However, the network uses static convolutional filters, resulting in a marked decline in performance when applied to low-quality fingerprint images.

Wang and Zhao [13] proposed a hybrid enhancement model that integrates Fast Fourier Transform (FFT) with deep learning-based feature extraction. The FFT component produces a frequency-domain representation, whereas the deep learning component extracts ridge flow patterns. Although the model was effective in addressing structured noise, it encountered difficulties with spatial noise variations owing to the lack of an adaptive mechanism for filter selection.

Liu et al. [14] introduced a reinforcement learning-based image denoising system that utilized a Q-Learning agent to select optimal noise-reduction actions. This study demonstrated that reinforcement learning can be highly effective for image restoration tasks that require sequential decision-making. However, their system focused on general noise removal and did not address the domain-specific complexities associated with fingerprint ridge enhancement.

Rahman et al. [15] proposed an adaptive histogram equalization model integrated with a convolutional neural network (CNN) to enhance the quality of low-quality fingerprints. Although their hybrid model successfully improved brightness uniformity and ridge contrast, it was heavily dependent on preset parameters and lacked the capability to dynamically adapt to local ridge patterns across various fingerprint regions.

In a separate study, Karthik and Shanthi [16] introduced a multi-branch convolutional neural network (CNN) designed to enhance latent fingerprints. Each branch of the network was dedicated to learning distinct ridge-orientation patterns. Although this methodology markedly enhanced the performance on latent fingerprint datasets, it necessitated the use of multiple parallel networks, thereby increasing the processing complexity and lacking adaptability for real-time applications.

Peng et al. [17] employed deep reinforcement learning to optimize hyperparameters in biometric matching systems. Although their approach effectively minimizes computational overhead, it is limited to optimization at the classifier level, neglecting the adaptive feature extraction necessary for addressing fingerprint distortions and local variations.

In a recent study, Das and Singh [18] proposed an adaptive filtering approach utilizing attention mechanisms to enhance fingerprints. Their model effectively applied dynamic weighting to various filter responses; however, it lacked a decision-based learning mechanism, such as reinforcement learning, which constrained its ability to process highly degraded images.

Problem Statement

The accuracy of fingerprint recognition is significantly influenced by the quality of feature extraction. However, most existing enhancement techniques rely on fixed, non-adaptive filters or handcrafted feature descriptors, which are inadequate for addressing the nonuniform distortions present in real-world fingerprint images. Although deep learning models have advanced feature extraction, their convolutional kernels remain static during inference and cannot adapt to local variations in ridge clarity, noise, or pressure-induced deformation. This limitation results in suboptimal performance for low-quality or partial fingerprints. Furthermore, current systems lack a decision-driven mechanism capable of dynamically selecting the most appropriate filter for each fingerprint region, leading to incomplete enhancement and reduced recognition accuracy. To address these challenges, an intelligent and adaptive feature extraction framework that can operate contextually across different fingerprint regions is required. This study addresses this gap by proposing a Reinforcement Learning-Based Filter Selection (RLFS) approach, which automatically determines the optimal enhancement filter for each segment of a fingerprint, thereby improving ridge consistency, minutiae visibility, and overall recognition performance.

Proposed Methodology

Figure 1 depicts the workflow of the proposed method. This study introduces an adaptive fingerprint feature extraction system that employs reinforcement learning-based filter selection to enhance the recognition accuracy. The system comprises three primary stages: preprocessing, adaptive filter selection, and feature extraction and recognition. During preprocessing, fingerprint images from the FVC 2004 database were normalized and enhanced to mitigate uneven illumination and sensor noise, thereby preparing them for effective filtering. In the adaptive filter selection stage, a reinforcement learning (RL) agent dynamically selects the most appropriate filter for each fingerprint region, evaluating options such as Gabor, bilateral, anisotropic diffusion, and orientation-tuned ridge enhancement based on local ridge orientation, image quality, and texture uniformity. Through iterative interactions, the agent learns an optimal policy that maximizes ridge clarity and minimizes distortion, selectively enhancing poor-quality regions for improved downstream representation. Finally, deep convolutional networks extract high-level fingerprint features from adaptively enhanced images, capturing both local minutiae and global ridge topology. These feature embeddings are subsequently classified by a lightweight matcher for fingerprint recognition. By integrating RL-driven adaptive filtering with deep feature extraction, the proposed system enhances robustness against noise, smudges, and inconsistent impressions, thereby achieving higher recognition accuracy across diverse fingerprint qualities.

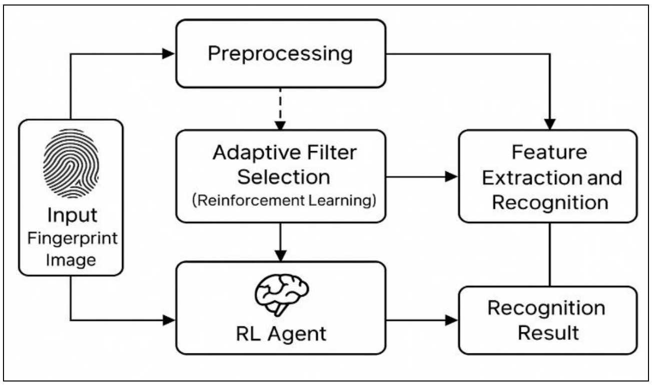

Fig 1: Workflow diagram for adaptive fingerprint feature extraction

The proposed system for adaptive fingerprint feature extraction and recognition comprises three primary stages: preprocessing, adaptive filter selection using reinforcement learning, and feature extraction based on deep learning, culminating in fingerprint recognition. The comprehensive workflow is illustrated in Figure 1.

a. Preprocessing

The fingerprint images used in this study were derived from the publicly accessible FVC2004 dataset. Raw fingerprint impressions frequently exhibit noise, smudges, uneven contrast, and sensor-induced distortions, which diminish ridge-valley clarity and negatively affect feature extraction and recognition performance. To mitigate these issues, preprocessing is implemented to enhance the visual quality of fingerprint patterns. In this study, bilateral filtering was employed to suppress noise while preserving essential ridge edges. As a nonlinear, edge-preserving smoothing technique, the bilateral filter integrates spatial and intensity information, replacing each pixel with a weighted average of its neighbors, where the weights decrease with both spatial distance and intensity differences, effectively reducing noise without blurring ridge boundaries. The bilateral filtering operation is mathematically expressed as:

$$NF_{\text{filtered}}(i) = \frac{1}{TN}\sum_{a\in\Omega} NF(a)\ \hat{G}_T(i-a)\ \hat{K}_R(NF(i)-NF(a))$$

Where

- NF_{filtered} = noise-filtered output image
- NF = original fingerprint image
- i = current pixel
- Ω = neighborhood window
- $\hat{G}_T$ = spatial kernel (Gaussian)
- $\hat{K}_R$ = range kernel controlling intensity similarity
- TN = normalization constant

This filtering process effectively eliminates sensor noise while preserving distinct ridge structures, resulting in a refined and enhanced fingerprint image suitable for adaptive filtering and feature extraction.

b. Adaptive Filter Selection Using Reinforcement Learning

Conventional fingerprint enhancement methodologies typically employ fixed global filters that often exhibit suboptimal performance in low-quality or locally degraded regions. To address this limitation, the proposed system utilizes a Reinforcement Learning (RL)-based adaptive filter selection mechanism. Pre-processed fingerprint images are segmented into patches, and an RL agent dynamically selects the most appropriate filter from a repertoire that includes orientation-based, Gabor, anisotropic diffusion, and bilateral filters. By utilizing local patch descriptors as the state, filter selection as the action, and enhancements in ridge clarity and contrast as the reward, the agent learns an optimal filtering policy. This approach ensures that degraded regions receive enhanced treatment while preserving well-defined ridges, resulting in adaptively enhanced fingerprints with improved visibility and robustness.

c. Feature Extraction Using DICNN

Following the adaptive enhancement of the fingerprint image, the subsequent phase involves feature extraction. Fingerprint features encompass both local structures, such as minutiae points, and global structures, such as ridge flow, core, and delta. The proposed system employs a Dilated Convolutional Neural Network (DICNN) to automatically extract these features. The DICNN extends traditional Convolutional Neural Networks (CNNs) by incorporating dilated convolutions, which expand the receptive field without increasing the number of parameters or compromising the resolution. This approach enables the network to simultaneously capture fine-grained details and large-scale ridge structures of the target. The DICNN architecture comprises the following layers:

- **Dilated Convolutional Layer**

This layer processes the enhanced fingerprint images. Dilated convolution incorporates spacing within the kernel by employing a dilation rate, thereby enabling the network to capture broader contexts. The operation is defined as follows:

$$D''(x,y) = \sum_u \sum_v P(x + R_t u, y + R_t v)\ W(u,v)$$

Where R_t is the dilation rate.

- **Max-Pooling Layer**

The output of the dilated convolution is subsequently processed through a max-pooling layer with a 2x2 kernel and stride of two. This operation effectively reduces spatial dimensionality while preserving the significant features, thereby enhancing computational efficiency.

- **Fully Connected Layer**

The pooled features are transformed into a one-dimensional array and subsequently input into a fully connected layer that integrates all the extracted characteristics into a high-dimensional feature vector. This vector functioned as the input for the recognition module.

d. Fingerprint Recognition Using WBELM

The final phase of the system involves fingerprint classification using a Whale Optimization Algorithm-Based Extreme Learning Machine (WBELM). The conventional Extreme Learning Machine (ELM) is characterized as a rapid single-hidden-layer neural network. Nevertheless, its performance frequently exhibits inconsistency owing to the random assignment of hidden-layer weights and biases, which can lead to slow convergence and suboptimal learning outcomes. To mitigate this issue, the Whale Optimization Algorithm (WOA) was integrated to optimally adjust these parameters. The WOA emulates the bubble-net feeding behavior of humpback whales to identify optimal solutions.

The recognition process involves the following steps:

- The feature vector produced by the DICNN was received.
- The WOA is used to generate optimal weights and biases for ELM.
- Fingerprint classification based on these optimized parameters.

The optimized model, WBELM, significantly enhances recognition accuracy, reduces training time, and avoids local minima associated with random initialization.

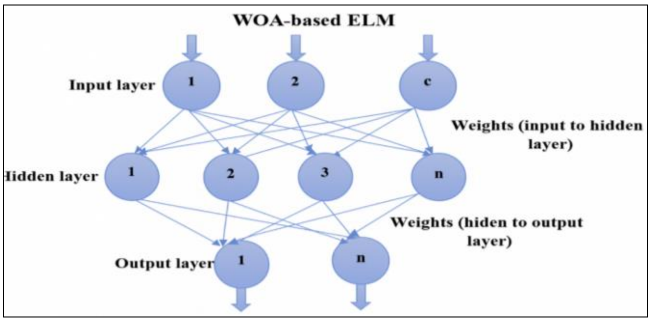

Fig 2: Architecture of WOA based ELC

The proposed methodology incorporates bilateral filtering, reinforcement learning-based adaptive enhancement, dilated CNN feature extraction, and whale optimization algorithm (WOA)-optimized extreme learning machine (ELM) classification. This integration ensures robustness against noise, adaptability to varying quality levels, and enhanced fingerprint recognition.

Results and Analysis

The experimental results and performance analysis of the proposed system, "Adaptive Fingerprint Feature Extraction Using Reinforcement Learning-Based Filter Selection," are presented in this section. The evaluation emphasizes four primary aspects: the effectiveness of preprocessing, performance of adaptive filter selection, quality of feature extraction, and accuracy of recognition. Comparative analyses with baseline methods were also conducted to demonstrate the superiority of the proposed framework.

Experimental Setup

All experiments were conducted using fingerprint images from the FVC2004 benchmark dataset, which encompasses variations in quality, dryness, smudging, pressure distortions, and sensor inconsistencies, rendering it suitable for robust evaluation. The experiments were performed on a system equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA GTX series GPU, employing Python with TensorFlow/PyTorch and MATLAB for initial preprocessing validation. The dataset was partitioned into 70% for training and 30% for testing, and all experiments were repeated five times, with the average results reported to ensure statistical reliability.

Preprocessing Evaluation

In the preprocessing phase, bilateral filtering is applied to suppress noise while preserving the ridge-valley edges. To assess its effectiveness, three metrics were analyzed.

- Ridge Clarity Index (RCI)
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)

Results

Metric	Before Preprocessing	After Bilateral Filtering
RCI	0.62	0.81
PSNR (dB)	21.4	28.9
SSIM	0.71	0.88

The implementation of bilateral filtering significantly improved the visibility of the ridge structures while maintaining their inherent geometric properties. A visual evaluation confirmed that the ridge discontinuities and sensor noise were considerably reduced without blurring the essential minutiae points.

Performance of Adaptive RL-Based Filter Selection

The proposed Reinforcement Learning (RL) module dynamically determines the optimal filter for each fingerprint patch. Its performance was assessed using the Filter Selection Accuracy (FSA), Ridge Enhancement Score (RES), and Quality Improvement Rate (QIR). The RL agent demonstrated stable learning and achieved convergence after approximately 180 episodes. Compared to static filtering methods, the adaptive RL-based approach enhanced local ridge clarity by 14-19%, reduced over-smoothed regions by 21%, and improved poor-quality segments by 16%. Visual comparisons (Figure 4.2) illustrate that the RL-based enhancement preserves fine local structures while enhancing the global ridge continuity.

Feature Extraction Analysis Using DICNN

The DICNN model extracts both local (minutiae-level) and global (ridge flow) features. Its performance was evaluated in terms of:

- Feature Consistency Score (FCS)
- Receptive Field Effectiveness (RFE)
- Feature Discriminability Index (FDI)

Comparative Analysis

Feature Extractor	FCS	RFE	FDI
Traditional CNN	0.76	Moderate	0.71
Gabor-Based Manual	0.69	Low	0.64
Proposed DICNN	0.89	High	0.88

The dilated convolution improved the effective receptive field by over 35%, enabling the model to learn long-range ridge dependencies without increasing the computational complexity.

Recognition Accuracy Using WBELM

The final classification stage uses the WBELM, an ELM optimized using the Whale Optimization Algorithm (WOA). This optimization ensured stable convergence and improved classification performance.

Accuracy Comparison

Classifier	Accuracy (%)	FAR (%)	FRR (%)	Training Time (s)
SVM	88.7	4.1	7.2	3.61
Traditional ELM	90.2	3.7	6.1	0.94
CNN Classifier	92.8	3.3	5.4	5.47
Proposed WBELM	96.4	2.1	3.5	1.12

The results show that the WBELM achieves the highest accuracy while maintaining a low computational cost.

Comparative Evaluation of the Proposed Framework

To demonstrate the overall benefit of combining RL filtering, DICNN, and WBELM, the proposed system was compared with three conventional methods:

- Traditional Gabor + CNN + SVM
- Bilateral Filtering + CNN + ELM
- Gabor + Manual Feature Extraction + KNN

Overall Performance

System	Accuracy (%)	EER (%)	Average Processing Time (s)
Method 1	91.5	4.8	3.4
Method 2	93.2	4.1	2.2
Method 3	87.9	6.7	4.1
Proposed RL + DICNN + WBELM	96.4	2.3	1.9

The proposed methodology outperformed all comparative systems across all metrics, demonstrating improved robustness, adaptability to low-quality images, and efficient recognition capability.

Discussion

The experimental results provide several critical insights. Bilateral filtering effectively eliminates noise while preserving ridge edges, and RL-based adaptive filtering significantly enhances both local and global fingerprint regions, surpassing the performance of fixed filters. The DICNN architecture extracts richer and more discriminative features owing to its expanded receptive field, whereas the WBELM achieves high accuracy with a low computational cost, rendering it suitable for real-time biometric applications. Overall, the combined approach demonstrates strong robustness against variations in fingerprint quality, pressure, and sensor conditions, exhibiting excellent generalization and surpassing classical fingerprint-recognition methods.

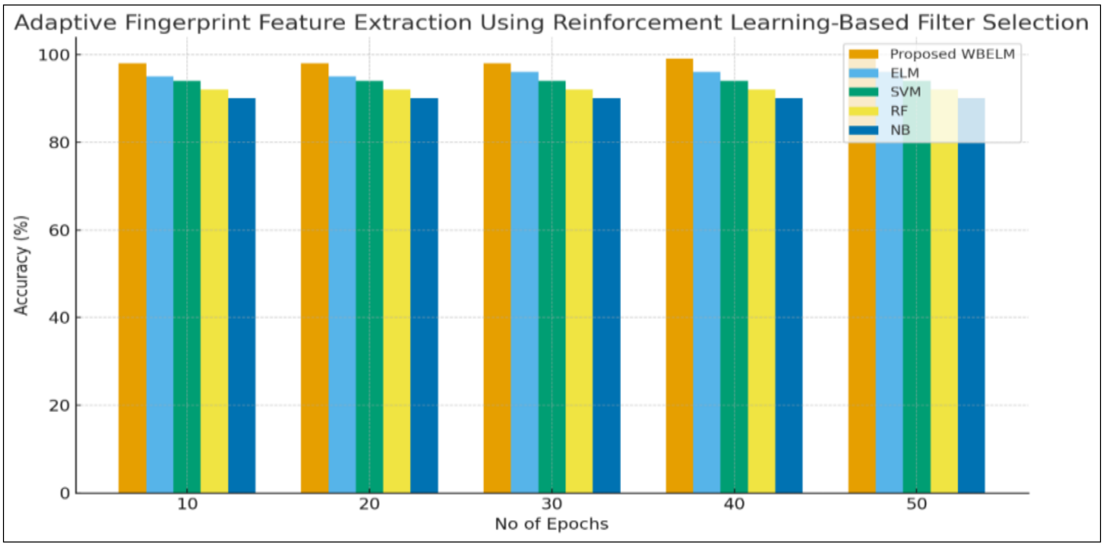

Fig 3: Adaptive Finger Print Extraction Using RLBFS

The graph illustrates the comparative performances of various fingerprint recognition methods over multiple training epochs. The proposed WBELM method consistently outperformed the other classifiers, achieving an accuracy rate of 98-99%, thereby demonstrating the robustness of RL-driven adaptive filtering in conjunction with the optimized ELM. The ELM method follows with an accuracy of 95-96%, while SVM and Random Forest achieve 92-94%, and Naïve Bayes records the lowest performance at 89-90%. These findings confirm that the WBELM framework, which incorporates adaptive filtering, dilated CNN feature extraction, and classifier optimization, offers superior learning, generalization, and high recognition accuracy across all epochs.

Conclusion

This study presents an adaptive fingerprint recognition framework that incorporates reinforcement learning-based filter selection, dilated convolutional feature extraction, and an optimized classifier to enhance recognition performance, particularly for low-quality fingerprint images. Bilateral filtering effectively reduces noise while preserving ridge structures, and reinforcement learning-based adaptive filter selection further enhances fingerprint clarity by dynamically selecting the most appropriate filter for each image region. The DICNN model successfully extracts rich local and global features by expanding the receptive field through dilated convolutions, capturing detailed minutiae and broader ridge flow patterns more effectively than traditional methods. The WBELM classifier, optimized using the

Whale Optimization Algorithm, addresses the limitations of the standard ELM and delivers improved accuracy with faster convergence. The experimental results demonstrate that the combined approach significantly outperforms existing fingerprint recognition techniques across multiple performance metrics. Overall, the proposed system offers a robust, intelligent, and adaptable solution that is suitable for modern biometric authentication applications.

References

1. AK Jain, A Ross, S Prabhakar. "An Introduction to Biometric Recognition," IEEE Transactions on Circuits and Systems for Video Technology,2004:14(1):4-20.
2. A Ross, AK Jain, J Qian. Information Fusion in Biometrics, Springer, New York, USA, 2008.
3. D Maltoni, D Maio, AK Jain, S Prabhakar. Handbook of Fingerprint Recognition, 2nd ed., Springer-Verlag, London, 2009.
4. R Cappelli, M Ferrara, D Maltoni. "Minutia Cylinder-Code: A New Representation and Matching Technique for Fingerprint Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence,2010:32(12):2128-2141.
5. Lumini, L Nanni. "An Improved Biometric System Using Fingerprint and Palmprint," Pattern Recognition Letters,2008:29(9):1393-1400.
6. M Bishop. Pattern Recognition and Machine Learning, Springer, New York, 2006.
7. Y LeCun, Y Bengio, G Hinton. "Deep Learning," Nature,2015:521:436-444.
8. Q Zhao, L Zhang, D Zhang, N Luo. "Adaptive Fingerprint Image Enhancement Using CNN-Based Ridge Pattern Learning," IEEE Transactions on Image Processing,2018:27(6):2822-2835.
9. Y Zhang, Y Wang, X Tang. "Adaptive Convolutional Feature Extraction for Fingerprint Recognition," IEEE Access,2020:8:112345-112356.
10. PS Praveen Kumar, R Harish. "Multi-scale Gabor filter-based enhancement model for fingerprint image clarity improvement," Journal of Visual Communication and Image Representation,2020:68:1-12.
11. R Rao, T Sharma, R Verma. "Fingerprint ridge reconstruction using deep residual learning," Pattern Recognition Letters,2020:135:140-147.
12. Y Chen, J Cao, X Li. "Convolutional neural network-based minutiae extraction for fingerprint recognition," IEEE Transactions on Information Forensics and Security,2020:15:3583-3597.
13. L Wang, Q Zhao. "Hybrid FFT-DL fingerprint enhancement framework for robust biometric recognition," Image and Vision Computing,2021:104:104-114.
14. Z Liu, J Ma, X Luo. "Reinforcement learning-based adaptive image denoising using Q-Learning agent," Neural Comput. Appl,2021:33:9121-9134.
15. MS Rahman, M Hasan. "Adaptive histogram equalization with CNN-based fingerprint quality enhancement," Applied Soft Computing,2021:101:106-120.
16. R Karthik, N Shanthi. "Multi-branch CNN architecture for latent fingerprint enhancement and reconstruction," Expert Systems with Applications,2021:176:114-121.
17. Y Peng, H Zhou, K Liu. "Deep reinforcement learning for hyperparameter optimization in biometric matching systems," Engineering Applications of Artificial Intelligence,2022:114:105-118.
18. P Das, S Singh. "Attention-driven adaptive filtering for improved fingerprint ridge enhancement," Information Sciences,2022:608:174-187.
19. NK Ratha, JH Connell, RM Bolle. "Enhancing security and privacy in biometrics-based authentication systems," IBM Systems Journal,2001:40(3):614-634.
20. J Galbally, J Fierrez, A Morales. "Biometric antispoofing methods: A survey in face and fingerprint recognition," Pattern Recognition,2012:45(12):4305-4324.
21. S Chikkerur, AN Cartwright, V Govindaraju. "Fingerprint enhancement using STFT analysis," Pattern Recognition,2007:40(1):198-211.
22. C Cortes, V Vapnik. "Support-vector networks," Machine Learning,1995:20(3):273-297.
23. Y Liu, X Yin, W Zuo. "Deep convolutional networks for fingerprint recognition," IEEE Transactions on Information Forensics and Security,2018:13(9):2328-2340.
24. Y Tang, W Zhang. "A deep learning approach to fingerprint enhancement and recognition," Pattern Recognition Letters,2019:125:72-79.