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RESEARCH ARTICLE

FINGERPRINT RECOGNITION AND AUTHENTICATION VIA ATROUS SPATIAL PYRAMID POOLING INFUSED MODULAR NEURAL NETWORK

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Abstract – Fingerprint recognition is a vital biometric technology employed in various security systems due to its high reliability and uniqueness. This paper presents a novel FINGPRA-NET for fingerprint recognition system based on deep learning. The proposed fingerprint recognition algorithms that incorporate feature extraction, pattern matching, and deep learning techniques to enhance recognition accuracy and computational efficacy. Initially, the gathered images are denoised using Laplacian filter to highlight regions of fast intensity variation in an image, which is useful for detecting the edges. The atrous spatial pyramid pooling (ASSP) layer is integrated in deep learning based modular neural network to enhance the performance and generalization capabilities of the model. This combination leverages the strengths of both ASPP (for capturing context at multiple scales) and MNN (for specialized detection tasks), resulting in improving the accuracy in fingerprint recognition. Coyote Optimization Algorithm (COA) is used to find the best correspondences between minutiae points in different fingerprint images. The experimental fallouts prove that the proposed FINGPRA-NET method achieves an overall accuracy of 98.92% outperforming traditional methods. The high accuracy and low error rates signify the model's effectiveness in distinguishing between authentic and non-authentic fingerprints.

Keywords *– Fingerprint recognition, Deep learning, Modular neural networks, Biometrics, Coyote optimization, Security systems.*

1. INTRODUCTION

Fingerprint is a biometric device that recognizes and authenticates individuals based on their unique fingerprint patterns. This technique makes use of the characteristic ridges and valleys on human fingertips, which are particular to each person and remain unchanged over time [1]. The process of fingerprint recognition involves capturing a digital image of a fingerprint, known as a fingerprint scan, and converting this image into a mathematical representation through feature extraction [2]. Key features, such as minutiae points (specific points where ridges end or bifurcate), are identified and used to create a unique fingerprint template [3]. Then in order to confirm a person's identification, this template is linked to previously stored templates within a dataset [4].

The fingerprint recognition process offers several advantages, such as high accuracy, ease of use, and cost-effectiveness [5]. Its non-intrusive nature makes it a preferred choice for many organizations seeking reliable and efficient security solutions [6]. Expertise advancements have also spawned more complex algorithms and sensors, that improve fingerprint identification systems' precision and velocity [7]. Despite its benefits, fingerprint recognition also faces issues like the potential for false positives or negatives, the need for high-quality fingerprint scans, and concerns over privacy and data security [8]. In order to get over these challenges and improve the fingerprint recognition system's resilience and dependability, research and development is currently occurring [9]. Deep learning-based fingerprint recognition is a major breakthrough in biometric identification technology that allows complicated information to be automatically extracted from fingerprint images [10]. Compared to conventional approaches, fingerprint identification systems can achieve improved accuracy, resilience, and adaptability by applying deep learning techniques [11]. Deep learning models' automatic feature extraction capabilities greatly lessens the requirement for expert knowledge during the feature construction process in the context of fingerprint identification [12]. This approach does deals with the need for manual feature extraction, which is a significant flaw in traditional fingerprint identification methods. An overview of this work's primary contribution is provided below,

- The proposed fingerprint recognition system utilizes a Laplacian filter to denoise the gathered fingerprint images for enhancing the edges.
- The inclusion of the ASSP layer in the deep learning-based modular neural network allows the model to capture context at multiple scales.

- The coyote optimization algorithm is used to optimize the matching process of minutiae points between different fingerprint images.
- This optimization improves the accuracy of fingerprint matching, ensuring that the proposed system is reliably identify correspondences between fingerprint features for security systems.

The remaining tasks have been scheduled as follows: Several recent studies on image retrieval are presented in Section 2. A comprehensive explanation of the suggested fingerprint recognition method is provided in Section 3. In Section 4, the implications of the proposed system are discussed. Section 5 provides an explanation of the conclusion and future scope.

2. LITERATURE SURVEY

In 2023, Chhabra., et al., [13] created a Convolutional Neural Network (CNN) with deep learning to enhance the automatic separation and recognition of latent fingerprints. This approach outperforms a naive convolutional neural network for image recognition and segmentation by using a pre-trained CNN with a stack of automatic coders. This model used the IIIT-D database and achieved a 98.45% segmentation accuracy for excellent images.

In 2023 Grosz and Jain [14] developed an AFRNet, incorporates attention layers for fingerprint identification into the ResNet design. Transformer-based fingerprint recognition is improved by this work in three ways: i) evaluating more attention-based frameworks; ii) expanding to bigger and more diverse datasets for training and evaluation; and iii) combining CNN-based and attention-based complementary representations to improve on previous fingerprint identification models.

In 2022 Heidari and Chalechale [15] introduced deep learning approach for human identification that utilizes dorsal features of the hand. This technique concentrates on the ring, middle, and index fingers' fingernails (FN) and finger knuckle prints (FKP). To improve authentication efficiency and bolster defenses against spoofing attacks, the approach employs a diverse set of biometric techniques. According to experimental findings, this suggested biometric system is more dependable, efficient, and resilient than alternatives now available.

In 2022 Trabelsi., et al., [16] presented an effective unimodal and multimodal fingerprint system based on deep learning and feature selection. This work primarily focuses on an enhanced version of PalmNet, termed PalmNet-Gabor, which is optimized for rapid identification of contactless and multispectral palmprint images. To improve the contrast of palmprint features, Log-Gabor filters were utilized during the denoising stage. Feature selection and dimensionality reduction techniques were then used to reduce the number of features. This proposed approach not only decreases computational time and feature count but also enhances the efficiency of PalmNet.

In 2021 Ahsan., et al., [17] introduced an intelligent computational method for autonomous fingerprint authentication for personal identification and verification. This method combines features from DL and Gabor filtering techniques to construct the feature vector. The feature vectors are subjected to Principal Component Analysis (PCA) in order to minimize overfitting and increase the categorization results' accuracy and dependability. The suggested approach outperformed the competition, obtaining a 98.89% accuracy rate.

In 2021 Shen., et al., [18] developed an RFFI technique for LoRa systems that combines spectrograms and a deep learning approach. Spectrograms are used in this method to depict the precise temporal-frequency characteristics of LoRa transmissions. The integrity of the system may be jeopardized by the drift in the instantaneous carrier frequency offset (CFO), which can also lead to an inaccurate categorization. To circumvent this, a hybrid classifier was designed that changes CNN outputs based on the estimated CFO. The maximum classification accuracy that could be obtained with this spectrogram-based method was 97.61%.

Despite advancements in fingerprint recognition, challenges remain. Deep learning models achieve high accuracy but demand substantial computational resources and large datasets, limiting real-time applicability. Integration of attention mechanisms adds complexity and may slow processing. Methods focusing on dorsal hand features may struggle with partial or low-quality prints. Techniques enhancing feature contrast can face challenges with environmental variations. Even accurate models are vulnerable to spoofing and may struggle with generalization across diverse fingerprint conditions.

3. PROPOSED METHODOLOGY

The main elements of the proposed FINGPRA-NET framework for accurate fingerprint recognition based on minutiae are described in this part, which also addresses template matching, minutiae feature extraction, and image preprocessing. Figure 1 shows a block diagram of the several modules and functions of the proposed structure.

3.1. Data pre-processing

The Laplacian filter is a derivative filter of second order that is utilized for edge detection in images by highlighting areas with abrupt changes in intensity. It is applied to fingerprint images to improve their borders and draw attention to discontinuities in the grey level, which helps to distinguish finer details. First, normalize and transform the fingerprint image to grayscale so that its intensity range is constant. The Laplacian Filter can be used to calculate the second derivative of the intensity values in the image. This will highlight the regions with high spatial frequency changes (edges). Then, subtract the Laplacian-filtered image from the original image to enhance the edges and reduce noise. The Laplacian operator is defined as:

$$\nabla^2 f(x,y) = \frac{\delta^2 f(x,y)}{\delta x^2} + \frac{\delta^2 f(x,y)}{\delta y^2} \tag{1}$$

By using the Laplacian filter for denoising, the critical features of a fingerprint image is enhance, making it easier to identify minutiae points for matching.

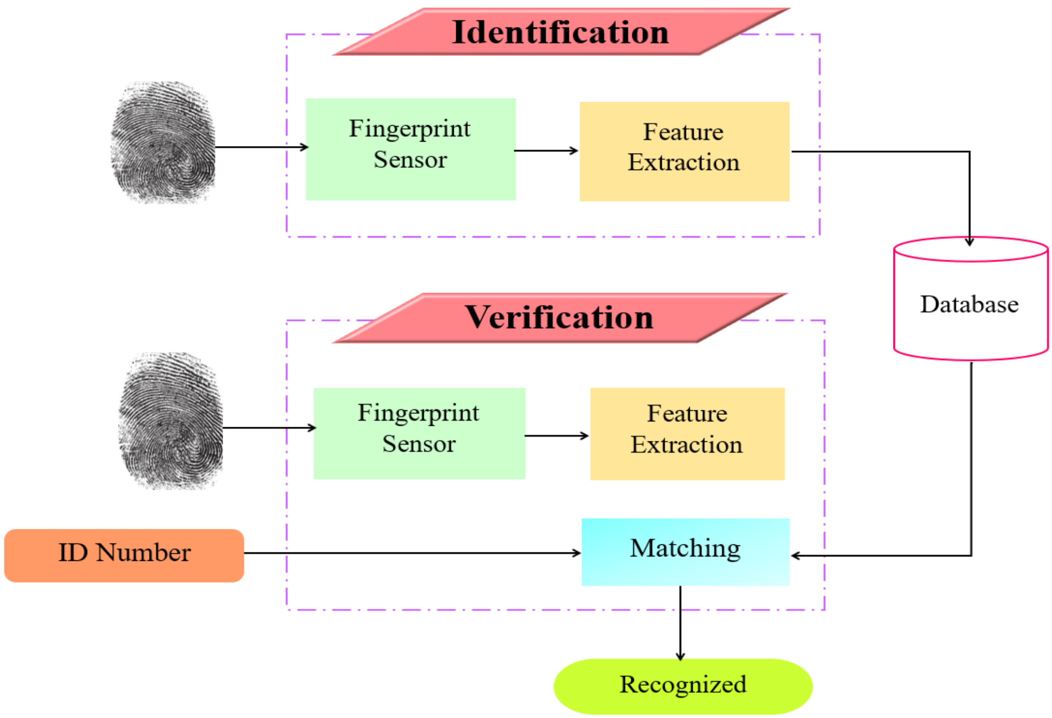

Figure 1. Proposed FINGPRA-NET Method

3.2. Minutiae feature extraction

The minutiae feature extraction using a modular neural network (MNN) involves designing a system where different modules of the network specialize in identifying specific subtle characteristics like bifurcations and ridge terminals. Integrating Atrous Spatial Pyramid Pooling (ASPP) with MNN can increase the process of recognition's precision and effectiveness.

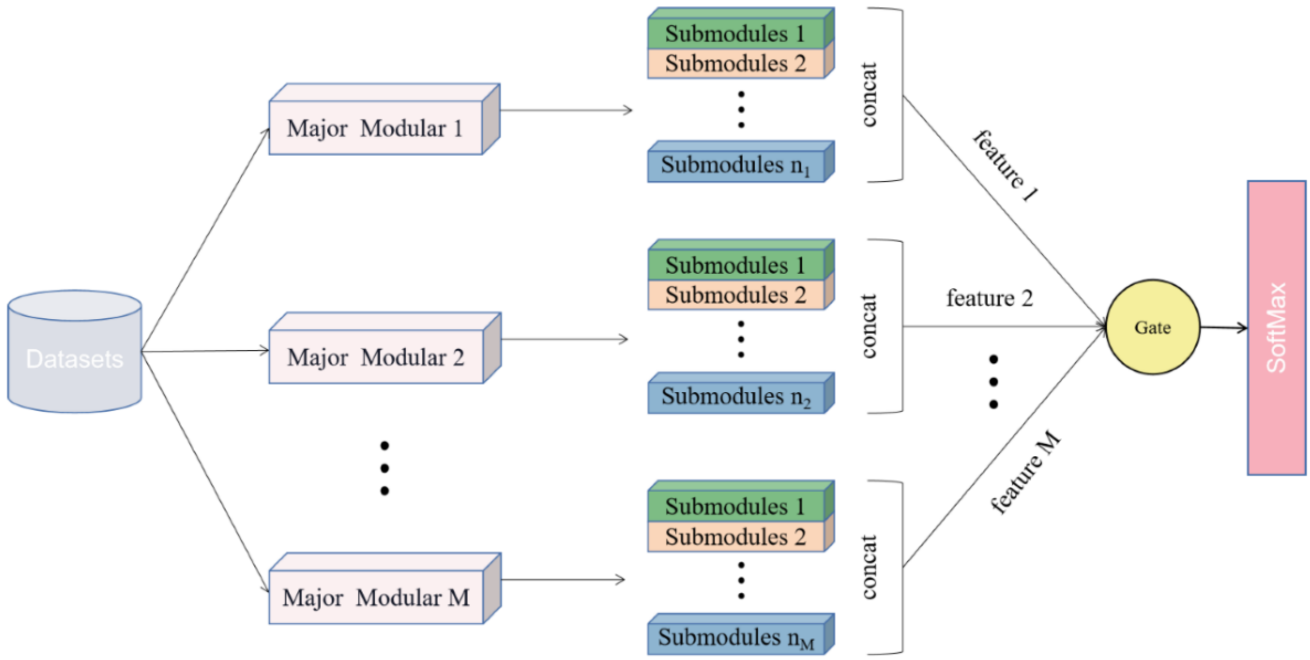

Figure 2. Architecture of ASSP-MNN for Minutiae feature extraction

ASPP is a technique used in Modular neural network (MNN) to capture multi-scale information by applying atrous (dilated) convolutions with different rates. This allows the network to understand context at multiple scales without reducing the resolution of feature maps. ASPP combines various dilation rates for atrous convolutions in order to extract multi-scale features. Let *f* is the feature map obtained from a previous convolutional layer. The ASPP module is defined as follows:

$$F_{as} = \{f_{d1}, f_{d2}, f_{d3}, f_{d4}\} \tag{2}$$

Where f_{di} is the feature map attained with the dilation rate d_i. For each atrous convolution with dilation rate d,

$$f_d(x, y) = \sum_{u=-U}^{U} \sum_{v=-U}^{V} w(u, v) \times f(x + du, y + dv) \quad (3)$$

Here $w(u, v)$ represents the convolutional kernel weights, and u, v are the kernel sizes. The modular neural network consists of multiple subnetworks, each responsible for detecting different minutiae types. Let M be the number of modules, and N_i be the i-th module. Each module N_i takes the ASPP feature map F_{as} as input and outputs the probability map P_i for a specific minutiae type.

$$P_i = N_i(F_{as}) \quad (4)$$

The overall minutiae map P_{min} is the combination of the outputs of all modules.

$$P_{min} = \sum_{i=1}^{M} P_i \quad (5)$$

By integrating ASPP within the MNN, multi-scale features are captured effectively and accurately detect minutiae points in fingerprint images. This combination leverages the strengths of both ASPP (for capturing context at multiple scales) and MNN (for specialized detection tasks), resulting in improving the accuracy in fingerprint recognition.

3.3. Feature matching algorithm

The Coyote Optimization Algorithm (COA) is a nature-inspired optimization algorithm based on the social and biological behaviour of coyotes. It was effectively applied to the problem of feature matching in fingerprint recognition, where the objective is to find the best correspondences between minutiae points in different fingerprint images. COA simulates the social structure and adaptability of coyote packs to find optimal solutions. The key steps in COA include initialization, fitness evaluation, adaptation, and pack update. The process continues until convergence or a stopping criterion is met. Initially, create an initial population of solutions (coyotes) within a pack. Each coyote represents a potential solution for minutiae matching between two fingerprint images.

$$C_i = \{(m_{1a}, m_{2b}) \mid a = 1,2, \dots . M_1, b = 1,2, \dots M_2\} \quad (6)$$

where m_{1a} and m_{2b} are minutiae points from the first and second fingerprint images respectively, and M_1 and M_2 are the quantity of small details in the two images. Evaluate the fitness of each coyote based on how well it matches minutiae points between the two fingerprint images. The fitness function $f(C_i)$ is defined based on the Euclidean separation between tiny points that match.

$$f(C_i) = \sum_{(m_{1a}, m_{2b}) \in C_i} \exp\left(-\frac{||m_{1a} - m_{2b}||^2}{2\sigma^2}\right) \quad (7)$$

here $||m_{1a} - m_{2b}||$ is the Euclidean distance between the exact locations that match, and σ is a parameter controlling the spread. By using the COA, fingerprint recognition systems was efficiently match minutiae features, leading to improved accuracy and robustness in identifying individuals based on their fingerprints.

4. RESULTS AND DISCUSSION

This section evaluates the effectiveness of the proposed strategy by implementing the experimental results using Matlab-2020b. Moreover, the comparison provides a detailed description and analysis of the total accuracy rate besides the efficiency of the proposed approach. Additionally, the proposed approach is contrasted with traditional deep learning models.

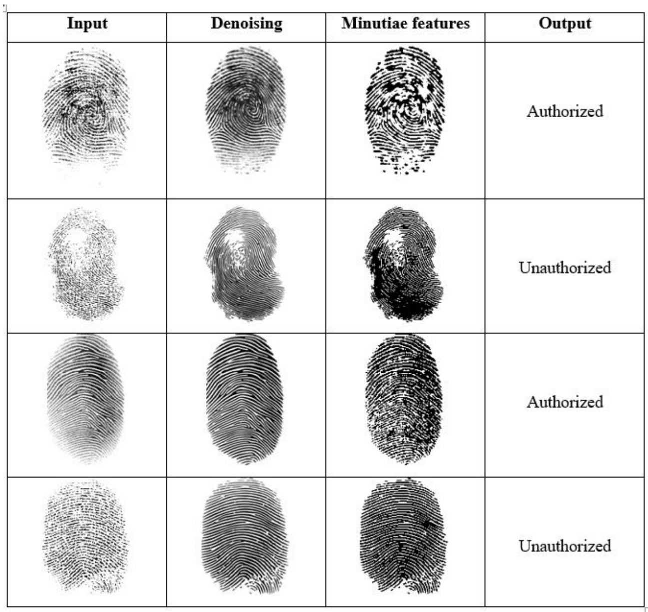

Figure 3. Experimental results of proposed fingerprint recognition system

Figure.3 portrays the fallouts of proposed FINGPRA-NET approach with the sample of images from available dataset to authenticate the finger print images.

4.1. Performance analysis

In analyzing the network parameters, such as precision (P), recall (R), F1 score (F1), accuracy (A), and specificity (S), the efficacy of the proposed approach was determined.

$$A = \frac{(TP+FP)}{(TP+TN+FN+FP)} \quad (8)$$

$$P = \frac{TP}{TP+FP} \quad (9)$$

$$S = \frac{TN}{TN+FP} \quad (10)$$

$$R = \frac{TP}{TP+FN} \quad (11)$$

$$F1 = 2\left(\frac{P*R}{P+R}\right) \quad (12)$$

where TP and TN denotes the real positive and negative aspects of the images, FP and FN provides false positives and negatives of the images. In this analysis, the competence of proposed and existing models was estimated using different metrics.

Table 1 shows the performance analysis of the proposed model with different network metrics.

A confusion matrix shows the actual versus expected classifications, which is used to assess how well a classification model performs.

Table 1. Performance analysis of the proposed model

Metric	Authenticate Users	Non-Authenticate Users
Accuracy	0.92	0.80
Specificity	0.94	0.78
Precision	0.91	0.82
Recall	0.89	0.77
F1 Score	0.90	0.79

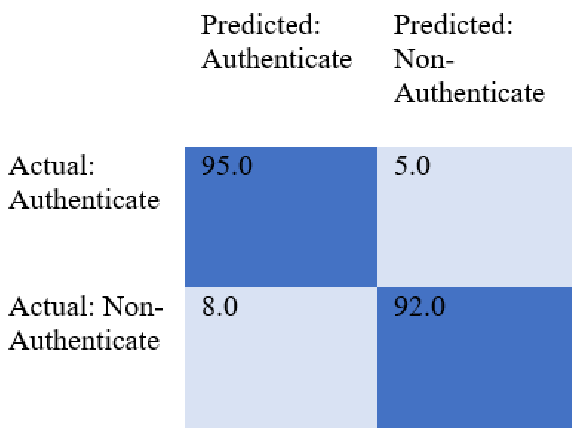

Figure 4. Confusion matrix of the proposed model

The figure 4 displays a confusion matrix for the proposed model, summarizing its classification performance. The matrix shows that out of all actual authenticate instances, 95% were correctly classified, while 5% were misclassified as non-authenticate. Conversely, for the actual non-authenticate instances, 92% were correctly identified, and 8% were incorrectly classified as authenticate. This confusion matrix illustrates how well the model distinguishes between authenticate and non-authenticate instances, as well as its accuracy and error rates.

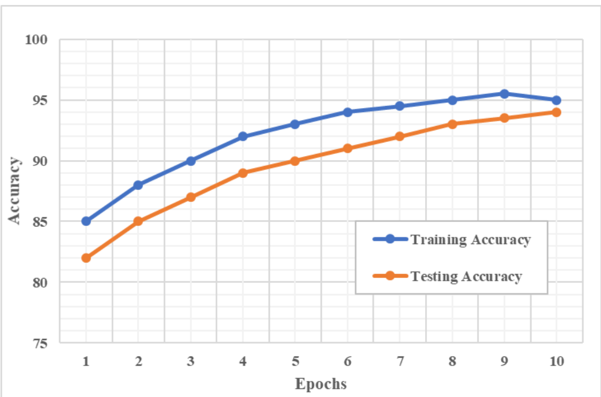

Figure 5. Accuracy curve of MNN

Figure 5 shows the training and testing accuracy curve for a fingerprint recognition model, with an average accuracy of 95.0%. The training accuracy starts lower but increases consistently, showing that the model is learning from the training data. The testing accuracy also increases over time, although it may not be as high as the training accuracy due to the model's exposure to unseen data. The final accuracies show a high performance close to 95%, which indicates a well-trained fingerprint recognition model with good generalization capability.

4.2 Comparative analysis

The comparison assessment was competed among the proposed MNN approach with different classification techniques. The comparison of traditional classification networks is illustrated in table.

Table 2. Performance comparison – MNN vs Traditional networks

Metric	CNN	ANN	RNN	MNN
Accuracy	0.88	0.81	0.82	0.95
Specificity	0.94	0.80	0.91	0.91
Precision	0.92	0.88	0.90	0.93
Recall	0.90	0.86	0.84	0.92
F1 Score	0.86	0.87	0.83	0.90

Table illustrates the performance of each model based on these network metrics. The proposed MNN shows slightly higher values in most metrics compared to the other models, suggesting potentially better performance in feature extraction process. Though, despite their utilization, classic DL networks didn't yield superior outcomes in comparison to the proposed MNN. The proposed MNN increases the overall accuracy by 7.03%, 14.21% and 13.87% better than CNN, ANN and RNN respectively.

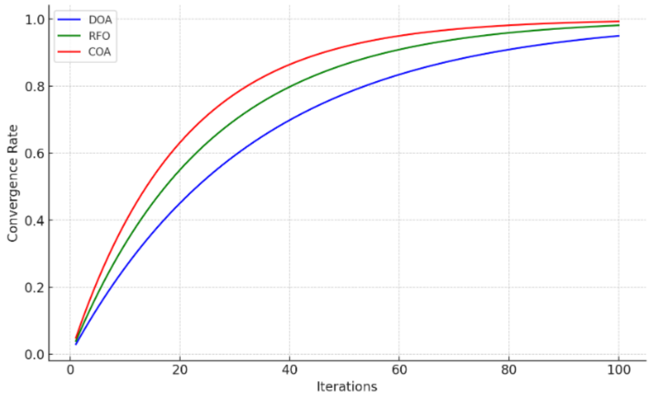

Figure 6. Convergence comparison between optimization algorithms

Figure 6 illustrates the convergence rate comparison among three optimization algorithms: Dingo Optimization Algorithm (DOA), Red Fox Optimization (RFO), and proposed Coyote Optimization Algorithm (COA). The convergence rate of DOA is relatively slower compared to COA and RFO. The proposed COA converges more quickly to an optimal or near-optimal solution, demonstrating the most rapid improvement in the early iterations. From this comparison, COA attains higher convergence rate that can quickly find a good solution and efficient matching of fingerprints especially in real-time systems.

Table 3. Accuracy Comparison-Proposed vs existing models

Authors	Method	Accuracy
Chhabra., et al., [13]	DL based CNN	98.45%
Ahsan., et al., [17]	DL+PCA	98.89%.
Shen., et al., [18]	RFFI scheme	97.61%
Proposed	xxx	98.92%

Table 3 demonstrates that for better outcomes, the accuracy values of the image must constantly be larger and the error rate should remain as minimal as practicable. The proposed model approach increases the overall accuracy of 0.16%, 0.35%, and 1.70% for DL-CNN [13], DL+PCA [17] and RFFI scheme [18] respectively. However, the existing networks are not attained good accuracy level contrasted to the proposed framework

5. CONCLUSION

In this paper, a novel FINGPRA-NET for fingerprint recognition system was presented that leverages deep learning to enhance accuracy and computational efficiency. By incorporating advanced feature extraction techniques, such as the Laplacian filter for denoising and edge detection, and the Atrous Spatial Pyramid Pooling (ASPP) layer for multi-scale context capture, our model demonstrates significant improvements in performance and generalization capabilities. The integration of these techniques within a modular neural network framework allows for specialized detection tasks, which are further optimized using the COA for accurate minutiae point correspondence. The experimental results showcase the efficacy of our approach, with the proposed model achieving an impressive overall accuracy of 98.92%, surpassing traditional fingerprint recognition methods. The proposed FINGPRA-NET model approach increases the overall accuracy of 0.16%, 0.35%, and 1.70% for DL-CNN [13], DL+PCA [17] and RFFI scheme [18] respectively. This high level of accuracy, coupled with low error rates, underscores the model's robustness in distinguishing between authentic and non-authentic fingerprints. In future, this work will be extended with further research and development, aimed at refining biometric authentication technologies for even greater reliability and efficiency.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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