Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 3, Issue 9, 2025

HYBRID DEEPEDGENET: A NOVEL MODEL INTEGRATING TRADITIONAL EDGE DETECTION TECHNIQUES WITH DEEP CONVOLUTIONAL NEURAL NETWORKS FOR ENHANCED FINGERPRINT ANALYSIS

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DOI: https://doi.org/10.5281/zenodo.17207282

Keywords
Hybrid DeepEdgeNet, Fingerprint Analysis, Edge Detection, Deep Convolutional Neural Networks, Bio-metric Identification

Article History
Received: 05 July 2025
Accepted: 15 September 2025
Published: 26 September 2025

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Abstract
Today, fingerprint recognition is the most used and reliable biometric identification and security system. However, traditional edge detection methods are not able to extract fingerprint pattern features from noisy images or complex fingerprint patterns. To tackle these challenges, we propose Hybrid DeepEdgeNet, a hybrid of conventional edge detection algorithms and deep convolutional neural networks (CNN) for fingerprint classification. We successfully integrate edge detection methods such as Roberts, Sobel and Prewitt with deep learning approach of multi scale feature extraction and CNN based feature enhancement using Hybrid DeepEdgeNet. The proposed approach is a combination of the classical approach and the deep learning approach, which can capture the detailed structure information from the fingerprint images and simultaneously learn the complicated patterns. A benchmark fingerprint dataset is used to further confirm the accuracy of the proposed model, achieving overall test accuracy of 96.897% and test loss of 0.215. In specifics, the model achieved 99.2% for ID classification, 96.9% for Gender and Hand classification, and 94.7% for Finger classification. To demonstrate the effectiveness of this model on various classification problems, these results suggest that the model's applicable in real-world biometric systems, where accuracy and stability are crucial. This work proposes the Hybrid DeepEdgeNet, a significant improvement to the fingerprint recognition paradigm, paving the way for future enhancements and the extension of this to other biometric modalities, thereby helping to define the future of secure and accurate identity authentication systems.

1. Introduction

In the past few years, biometric authentication has been improved greatly especially in the fingerprint recognition which is one of the most important techniques in the field of authentication systems [1]. Edge detection and minutiae extraction techniques have been investigated in the past as the main methods of fingerprint analysis. Nevertheless, the performances of these methods are limited in handling with complex fingerprint patterns, partial prints, and noise. On the other hand, models such as deep learning especially the convolutional neural networks (CNN) [2] have gained a lot of reputation in the field of computer vision such as in object detection as well as image classification. However, the use of CNNs in fingerprint recognition has been restricted due to their requirement of high data samples and their failure to capture the minutiae details that are very significant in fingerprint analysis [3]. Hybrid approach leverages the strengths of both methodologies: the accuracy of representing edges in fine details and the high features extraction from images of CNNs [4]. Hybrid model is intended to enhance the integration of features from such techniques to enhance classification, noise tolerance and system reliability [5].

Fingerprint recognition is one of the oldest biometric technologies with several applications and uses in law enforcement, border control, and access control systems [6]. In a report shared by Grand View Research, the global fingerprint sensor market was worth USD 3.54 billion in 2020 and is projected to reach a CAGR of 14.7% between 2021 and 2028 [7]. This widespread adoption provides a rationale for accurate and reliable fingerprint analysis [8]. Sobel, Canny and Prewitt are some of the oldest techniques that have been implemented to extract features from the fingerprint images by detecting the boundaries of ridges and valleys [9]. However, these methods have some problems when used in low quality image, the noise and distortion may result in incorrect feature extraction, which affects the recognition rate [10]. The drawback of the conventional style has led to the search for enhanced technique especially in deep learning. A common architecture utilized widely for image classification is the convolution neural networks CNNs feature hierarchy from more complex databases [13]. The study conducted in the recent past revealed that CNN-based models could reach an accuracy of 88% in fingerprint recognition tasks if done in perfect environment [12]. However, the study also pointed out the fact that CNNs might not be able to extract finer structural features of fingerprint patterns especially when the images are noisy or of low contrast [13]. This gap between conventional edge detection algorithms and deep learning models is a challenge in fingerprint analysis [14].

The rationale for this research lies in the urgent necessity to improve the effectiveness and efficiency of fingerprints as one of the biometric parameters [16]. Fingerprint recognition is used in many security applications because it is unique and easy to capture [17]. However, basic edge detection methods, which form the basis of extracting features from fingerprint images, present several challenges in issues to do with complex patterns, noise, and variations in image quality [18]. This paper will show that these challenges can change the recognition process of biometric systems thus threatening the security and efficiency of these systems [15]. Moreover, deep CNNs have been widely used and demonstrated remarkable performance in image analysis, however, fingerprint recognition is still new area of application for deep CNNs [19]. CNNs are good in learning hierarchical features from data but can fail to capture some of the important structural details that are very essential in fingerprint identification [20]. This research seeks to fill the gap between the conventional edge detection methodologies and the state-of-the-art deep learning techniques by proposing a combined model of both [21]. This paper aims to combine the traditional edge detection method into the CNNs for better enhancement of the feature extraction of the fingerprint images to increase the efficiency of biometric identification systems [22].

Fingerprint analysis is one of the most important methods of the biometric identification; however, the application of the edge detection in the case of the low quality or distorted fingerprint images caused by the noise and variations in the ridge patterns [23]. These limitations can result in a lower recognition accuracy and even lower reliability of the fingerprint recognition especially when the quality of fingerprints is low in real life situations. Thus, the demand for a reliable solution to augment feature extraction via traditional techniques and integrate state-of-the-art machine learning approaches to improve the performance of fingerprint analysis systems. To overcome these problems, the proposed Hybrid DeepEdgeNet model combines traditional edge detection with deep convolutional neural networks to help improve the precision and stability of fingerprint recognition regardless of the lighting conditions.

1.1 Formulation of Optimized Fingerprint Recognition

1.1.1 Optimized Feature Fusion in Hybrid DeepEdgeNet for Fingerprint Classification

The objective is to find out how the results can be optimized by a combination of edge detection and CNNs, while being immune to different fingerprint patterns. The problem is formulated as multi-objective optimization one in which the goal is to maximize the classification accuracy A while minimizing the computational complexity C. Let f_e (x) represent the feature vector obtained from edge detection, and f_c (x) represent the feature vector obtained from the CNN. The fusion function F(x) combines these features. The goal is to find the optimal fusion function $F^{\wedge}$ (x) that satisfies:

$$f_e(x) \quad \sum_{i=1}^{n_e} \alpha_i \cdot \left(\int_{\Omega_i} g_i(x) d\Omega_i + \sum_{j=1}^{m_i} \beta_{ij} \cdot h_{ij}(x) \right) \quad (1)$$

$$f_c(x) \quad \sum_{k=1}^{n_c} \gamma_k \cdot \left(\int_{\Psi_k} k_k(x) d\Psi_k + \sum_{l=1}^{p_k} \delta_{kl} \cdot l_{kl}(x) \right) \quad (2)$$

$$F(x) \quad w_1 \cdot f_e(x) + w_2 \cdot f_c(x) + \lambda \cdot \left(\frac{\partial \phi(x)}{\partial x} + \int_{\Theta} \phi(x) d\Theta \right) \quad (3)$$

$$A(F(x)) \quad \max_{\{w_1, w_2\}} \left\{ \frac{1}{N} \sum_{i=1}^{N} I(y_i = y_i) \right\} \quad (4)$$

$$C(F(x)) \quad \min_{\{w_1, w_2\}} \left\{ \sum_{i=1}^{N} \left[T_i(F(x)) + \sum_{k=1}^{n_i} \zeta_k \cdot \left(\frac{\partial^2 F_k(x)}{\partial x_k^2} \right) \right] \right\} \quad (5)$$

Objective Function: The objective function is to maximize accuracy while minimizing complexity:

$$\max_{w_1, w_2} [A(F(x)) - \lambda \cdot C(F(x))] \quad (6)$$

This problem formulation aims at combining the conventional edge detection technique with CNN to develop a novel fingerprint classification model. The challenge lies in balancing the contributions from both feature extraction techniques, as reflected in the fusion function F(x) in Equation (1). The accuracy and complexity functions are defined by Equations (2), (3), (4) and (5), respectively.

The final objective function in Equation (6) aims to find optimal weights w1 and w_2 to maximum classification accuracy with the least computational complexity.

1.1.2 DeepEdgeNet Training Optimization for Enhanced Feature Discrimination in Fingerprint Recognition

This formulation focuses on optimizing the training process of the DeepEdgeNet model, which combines edge detection with deep CNNs, to enhance feature discrimination in fingerprint recognition tasks. The primary objective is to minimize the training loss while maximizing feature discrimination, leading to improved identification and verification performance across diverse fingerprint datasets. The training process of DeepEdgeNet can be modeled as a constrained optimization problem, where the loss function L(θ) is minimized while ensuring that the feature discrimination D(f(x)) is maximized. Here, θ represents the model parameters, and f(x) is the feature map obtained from the hybrid network.

$$L(\theta) \quad \frac{1}{N} \sum_{i=1}^{N} L(y_i, y_i(\theta)) + \sum_{j=1}^{M} \lambda_j \cdot \|\theta_j\|_2^2 + \sum_{k=1}^{P} \mu_k \cdot |\theta_k| \quad (7)$$

$$D(f(x)) \quad \frac{1}{m} \sum_{s=1}^{m} \|f_s(x_i) - f_s(x_j)\|_2^2 \text{ for } x_i, x_j \in X, y_i \neq y_j \quad (8)$$

$$\max L(\theta) \quad \text{subject to } \max D(f(x)) \quad (9)$$

Objective Function: The objective function for this problem is:

$$\min[L(\theta) - D(f(x))] \quad (10)$$

This problem formulation focuses on optimizing the training of the DeepEdgeNet model by minimizing the loss function L(θ) in Equation (7) while simultaneously improving the feature discrimination as described in Equation (8). The objective function in Equation (9) and (10) achieves the right trade-off between loss minimization and feature discrimination maximization which is essential for a good and robust fingerprint recognition.

1.1.3 Multiscale Feature Integration in DeepEdgeNet for Robust Fingerprint Matching

This formulation discusses the use of multi-scale features within DeepEdgeNet model in the pursuit of improving the reliability of fingerprint matching. The goal is to fuse features that encode details of different resolutions, including high and low, to enhance the matching performance under different circumstances, such as partial prints or noisy data. The problem is how to join these multi-scale features in a correct way and reduce false match rates. The problem can be mathematically formulated as an optimization problem where the multi-scale feature integration function M(x) is designed to maximize the matching accuracy M_A and minimize the false match rate FMR. Let fs (x) denote the feature vector at scale s.

$$f_s(x) \quad \sum_{i=1}^{n_s} \alpha_{si} \cdot \left(\int_{\Omega_{si}} g_{si}(x) d\Omega_{si} + \sum_{j=1}^{m_{si}} \beta_{sij} \cdot h_{sij}(x) \right) \quad (11)$$

$$M(x) \quad \sum_{s=1}^{S} w_s \cdot \left(f_s(x) + \sum_{k=1}^{Q_s} \nu_{sk} \cdot \int_{\Lambda_{sk}} \frac{\partial f_s(x)}{\partial x} d\Lambda_{sk} \right) \quad (12)$$

$$M_A(M(x)) \quad \frac{1}{N} \sum_{i=1}^{N} I(y_i = y_i) + \sum_{j=1}^{R} \tau_j \cdot \left(\int_{\Gamma_j} M(x) d\Gamma_j \right) \quad (13)$$

$$FMR(M(x)) \quad \frac{1}{N} \sum_{i=1}^{N} \left[I(y_i \neq y_i \text{ and } y_i \in Y_s) + \sum_{l=1}^{V} \eta_l \cdot \frac{\partial^2 M_l(x)}{\partial x^2} \right] \quad (14)$$

Objective Function: The objective function is to maximize matching accuracy while minimizing false match rates.

$$\max_{w_s}\left[M_A\big(M(x)\big) - \lambda \cdot FMR\big(M(x)\big)\right] \qquad (15)$$

This problem formulation is concerned with improving the matching of fingerprints through multi-scale feature fusion in the DeepEdgeNet architecture. The features extracted at multiple scales make the model cover a larger range of fingerprint details, which would increase the resistance against partial or noisy fingerprint data. The objective function in Equation (15) is to strike a balance on the inputs from the different scales to get the best results in terms of the correct match with the least false matches so that there can be accurate fingerprint matching regardless of the conditions prevailing at that time.

This model aims at addressing the flaws of the traditional approaches and present a better solution for biometric fingerprint recognition particularly in adverse environment.

- To improve the feature extraction and the classification in the fingerprint area the proposal of the mixed model which would include the employ of classical methods for the edge detection and CNNs.
- To increase the accuracy of the selected fingerprint features by using both Edge detection and CNNs, especially when the image quality is low.
- To evaluate the performance of the proposed Hybrid DeepEdgeNet model against standard fingerprint datasets and compare it with other existing methods.
- To explain the applicability of the model in realistic cases, considering changes in the image quality and conditions for the functional biometric systems
- This research presents the Hybrid DeepEdgeNet model which comprises of the conventional edge detection model and deep convolutional neural networks (CNNs) to improve fingerprint analysis. The model solves problems of feature extraction and recognition accuracy and can be used as a solution for biometric systems.

1. **Hybrid Model Integration:** Proposing a new approach of the Hybrid DeepEdgeNet model to combine the existing edge detection techniques with CNN for better fingerprint feature extraction and recognition.
2. **Enhanced Accuracy:** Improved fingerprint recognition accuracy in terms of edge detection and deep learning especially in low-quality image conditions.
3. **Benchmark Evaluation:** Comparing the Hybrid DeepEdgeNet model with standard fingerprint datasets, the improvements in performance over baseline traditional and CNN methods are demonstrated.
4. **Practical Application:** Mitigating real-life problems through showing how the model performs well in different fingerprint conditions as well as variations in image quality and environmental conditions.
5. **Robustness and Efficiency:** Offering a model that increases the recognition accuracy while increasing computational efficiency and robustness of the system, which is suitable for practical biometric systems.

Fingerprint classification plays a very critical role in biometric security systems, demanding accuracy and robustness for reliable identification. Traditional methods, such as edge detection methods or CNNs, often struggle with the structural complexity and variability of fingerprint patterns. We propose a novel model called Hybrid DeepEdgeNet that combines edge detection techniques with deep learning for improved classification performance. This model achieve more accuracy across several tasks such as ID, Gender, Hand, and Finger classification with the utilization of multi-scale feature extraction, CNN-based feature refinement, and is going to discuss its design, implementation, and evaluation with potential prospects to contribute in the domain of fingerprint recognition for biometric applications.

2. Literature Review

Aboalhsan and M. N. Alatawi also investigated basic deep learning approaches that can be applied to fingerprint recognition, especially in enhancing the efficiency of fingerprint analysis systems. Their work also shows the application of deep learning models for pattern extraction within fingerprint data is crucial for accurate recognition. The effectiveness of deep learning in this context further justifies our work, in which we propose to integrate deep learning with the classic approach to edge detection in the Hybrid DeepEdgeNet model to improve the performances of fingerprint recognition systems [4]. D. L. Andreea-Monica et al. proposed a fingerprint matching algorithm that uses edge features together with

CNNs. Their approach also focuses on edge detection where the main fingerprint features are detected and then passed through CNNs for matching [5]. R. Chanklan et al. proposed a method of fingerprint recognition based on the utilization of edge detection and the dimensionality reduction. This research aims at minimizing the computational cost in the fingerprint recognition systems without compromising on the accuracy of the system by performing edge detection and dimensionality reduction [6]. The use of these techniques makes it possible to retain only the most relevant fingerprint features, which is especially important when working in conditions of limited resources [7]. This work is relevant to our study in the sense that it stresses the need to combine edge detection with sophisticated feature extraction techniques, which is a key idea behind the Hybrid DeepEdgeNet model proposed in our work [8]. A. Chowdhury et al. studied the ability of CNNs to learn the importance of the points of interest, which are important in fingerprint matching They show that their CNN is capable of detecting and sorting these minutiae points without the need for human intervention, which in turn enhances matching precision [9]. The results obtained from this study indicate that deep learning models can self-learn significant fingerprint features, a notion that the Hybrid DeepEdgeNet model aims at combining deep learning with edge detection to improve the fingerprint recognition accuracy [10].

U. U. Deshpande et al. proposed the CNNAI, a new algorithm for the latent fingerprint matching using a CNN and Nearest Neighbor Arrangement Indexing. Their method is designed for the purpose of raising the probability of latent fingerprints to be matched since the prints may be partial or of low quality. CNNs if used in conjunction with the indexing techniques, it is possible to match the images even in the worst-case scenarios [11]. H. Gu et al. also mentioned that there were some works on applying attention mechanisms to the RF fingerprinting, and with these techniques, the performance of machine learning models can be enhanced by paying more attention to the important parts of the input [12].

It is pointed out that the application of attention mechanisms in RF fingerprinting makes identification more precise and resistant to noisy environment [13]. He et al. also suggested that the integration of Gabor filters with the convolutional neural networks can be used for fingerprint classification [14]. Together with the orientation frequency information as extracted by Gabor filters, CNNs are incorporated to form a model that can accurately detect fine details on fingerprints. The results of the study confirm the possibility of using the hybrid models for biometric recognition when the benefits of the conventional methods may be applied to improve the learning capabilities of the deep networks [15]. Kumar and Tiwari put forward a biometric recognition using deep learning with features hybrid in nature. The authors' contributions are based on the discussion of the need to incorporate both handcrafted and learned features to enhance the performance of biometric systems. The following are the conclusions from their works, which support our further proposed model that is targeted at the development of the next level of hybrid feature integration [16].

To this end, Z. Li et al. introduced a new fingerprint recognition method based on Siamese neural network. This method is based on the concept of learning the similarity of two fingerprints which is useful when the system must learn with one or few samples. It is possible to state that the fact that the Siamese network can perform the matching on the fingerprints directly and not the extracted features differing it from other traditional methods prove the flexibility of the deep learning in fingerprints recognition process. Such innovative approaches will be further expanded in our research by applying the edge detection techniques to increase the accuracy and reliability of the matching processes [17]. S. Minocha et al. put forward a fingerprint recognition system using a CNN model that is designed to improve the fingerprint match rate and speed. His work emphasizes on the stability of CNNs in capturing challenges designs of the fingerprints, which is inherent for recognition. The success of this study to use CNNs in fingerprint recognition affirms the proposed plan of using CNNs [18]. Y. Mohamed et al. are more interested in enhancing ear biometrics through deep learning and as such, this work provides useful information on how deep networks can be enhanced to improve the Y. Mohamed et al. concentrated on improving ear biometrics with deep learning, providing important information on how deep networks can be trained to increase the accuracy and stability of biometrics. While their work is focused on ear biometric, the idea of improving feature extraction using deep learning is directly transferable to fingerprinting [19]. H. G.

Muhammad and Z. A. Khalaf proposed a fingerprint identification system using VGG, CNN, and ResNet of the most developed CNN architectures. They investigate the effectiveness of these architectures in fingerprint recognition and identify the advantages and limitations of each architecture. It is even more informative to use well-developed CNN architectures like ResNet for depth and feature extraction for our study. Hybrid model could be used to improve the performance of fingerprint analysis especially where the data is complex and high-dimensional as noted in [20].

Nguyen et al. developed a robust minutiae extractor that integrates deep networks with domain knowledge specific to fingerprints. Integrating deep learning with the conventional fingerprint domain knowledge, the study obtained a better performance in minutiae extraction which is very important for fingerprint matching. This approach shows that domain knowledge needs to be integrated into deep learning models for improving its performance on specific tasks [21]. It is the same philosophy our research adopts; to combine the best of edge detection techniques developed over the years with the current advancement in deep learning. The fusion of standard fingerprint recognition approaches with deep learning methods has been on the research agenda for quite some time. Nur-A-Alam et al. suggested an automatic fingerprint identification system based on feature fusion using Gabor filters and deep learning.

The work successfully integrates the capability of the Gabor filters in representing texture with the efficient pattern recognition of deep learning models to enhance the accuracy of fingerprint matching [22]. In the context of palmprint recognition, Putra et al. proved that edge detection features should be integrated with CNNs. This approach also enhanced the recognition accuracy and demonstrated the ability of the hybrid models in addressing variations in biometric data. The effectiveness of this method in palmprint recognition leads to the idea of applying similar techniques to fingerprint analysis [16]. P. B. S. Serafim et al. suggested the method for fingerprint segmentation using Convolutional Neural Networks (CNNs), their approach is based on the ability of correctly isolating fingerprint from the background noise which is very important in fingerprint recognition. The application of CNNs for segmentation shows that deep learning can be applied to different levels of fingerprint analysis [13]. X. Sing et al. proposed a novel CNN based framework for indoor localization using WiFi fingerprinting and shown the flexibility of CNN in applying to non-image data set, their work demonstrates that CNNs can be used in an optimal manner to extract and learn complicated spatial features of WiFi signal data, resulting in substantial enhancement of localization precision [15]. C. Yuan et al. were particularly interested in fingerprint liveness detection using an improved CNN with image scale equalization, a problem that is of great importance in terms of distinguishing between real and spoof fingerprints, this proposed method increases the effectiveness of a CNN in learning the distinctions between actual and forged fingerprints by normalizing the size of the input images. This work is relevant to our study because liveness detection is a critical component of fingerprint recognition systems [10]. Pandya et al. presented the fingerprint classification through deep convolutional neural networks and shown that CNN is useful for fingerprint classification based on the ridge pattern [22].

Fingerprint recognition previous studies have focused mainly on the classical edge detection algorithms such as Sobel, Roberts, and Prewitt, which obtain structural details but fail in handling complex variations. In contrast, CNNs demonstrated excellent performance in feature extraction with large datasets and often suffer from overfitting. Hybrid approaches have been used in recent studies, which merge traditional and modern techniques to reap the benefits of both. However, these approaches do not integrate seamlessly to enable robust classification across multiple tasks. Our work extends the foundations by developing a hybrid model that integrates edge detection with deep learning in a unified framework, thus showing improved accuracy and generalization.

3. Methodology

This section proposes a new Hybrid DeepEdgeNet model for fingerprint analysis and this section gives an overview of the proposed model. The paper is organized into several sub-sections that describe the dataset and data pre-processing, traditional edge detection techniques, proposed Hybrid DeepEdgeNet architecture and how the above components are combined to improve fingerprint recognition.

Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 3, Issue 9, 2025

3.1 Dataset
To assess the Hybrid DeepEdgeNet model, the FVC2002 dataset was used for the fingerprint verification and identification. The databases used in the study are four, namely DB1, DB2, DB3, and DB4, which include 100 fingerprint images each acquired at different resolutions and under different conditions. Each of the databases contains images of different quality, noise and partial prints which provide rich testing ground for the model. The dataset also contains ground truth minutiae details which is very important when it comes to testing the performance of our model.

3.2 Data Preprocessing
However, applying the edge detection and deep learning techniques, it is necessary to resharpen the fingerprints and establish the image standardization for the subsequent analysis. And among the preprocessing steps exist:

3.3 Image Normalization
Normalization is performed to standardize the intensity values of the fingerprint images, making them consistent for subsequent processing. Let I(x,y) represent the intensity of the pixel at position (x,y). The normalized image I_N (x,y) is computed as:

$$I_N(x,y) = \frac{I(x,y) - \mu_I}{\sigma_I} \quad (16)$$

where μ_I is the mean intensity and σ_I is the standard deviation of the pixel intensities in the image.

3.4 Image Enhancement
To improve the clarity of ridge structures, we apply a Gabor filter G(x,y;θ,f) that enhances the ridges while suppressing noise:

$$G(x,y;\theta,f) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos(2\pi f x'. + \phi) \quad (17)$$

where $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$, with θ representing the orientation of the filter, f the frequency, γ the spatial aspect ratio, σ the standard deviation, and ϕ the phase offset.

3.5 Segmentation
The fingerprint area is segmented from the background using a thresholding technique. Let $I_E(x,y)$ be the enhanced image. The segmented image $I_S(x,y)$ is given by:

$$I_S(x,y) = \begin{cases} 1 & \text{if} I_E(x,y) \geq T_s \\ 0 & \text{if} I_E(x,y) < T_s \end{cases} \quad (18)$$

where T_s is the segmentation threshold determined via Otsu's method. Data preprocessing is a crucial step in fingerprint analysis to enhance image quality and prepare the data for further processing. Below are the results of the various preprocessing steps applied to the fingerprint images from the dataset.

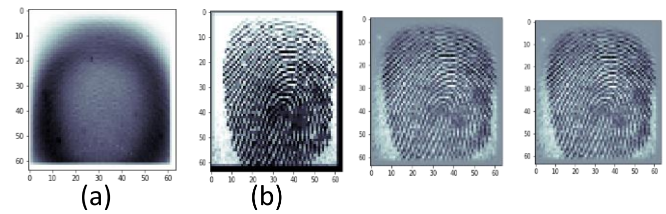

Fig.1. Pre-Processes Method for fingerprint analysis

The first process in the proposed method is shown in Figure [a], where the intensity of the fingerprint image is pre-processed by normalizing the intensity values. This helps to maintain homogeneity in the data that is required over all the data sets before any other operation is carried on. The fingerprint image after applying Gabor filter is shown in the Figure [b]. This step increases the contrast of the ridge so that the ridge structures will be much clearer than they were before. Segmentation is done to separate the fingerprint region from the background. The segmented image is shown in the following figure [c]. This step is important to narrow down a searching area where most important parts of an image are located. Lastly, the pre-processed fingerprint image is obtained as in Figure [d] which is suitable for edge detection. This is product of the preprocessing stage of the pipeline and is used as input for the next step which is edge detection.

3.6 Edge Detection Techniques
The filter used in this work is applied to carry out the conventional edge detection on the fingerprint images to obtain the ridge and valley structures. We employ three classical methods: Sobel, Canny and Prewitt, all of whom play a central role in capturing different structural characteristics.

3.7 Sobel Edge Detection
The Sobel operator computes the gradient magnitude $M_S(x,y)$ and direction $\theta_S(x,y)$ of the image intensity:

$$M_S(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)} \quad (19)$$

$$\theta_S(x,y) = \tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \quad (20)$$

where $G_x(x, y)$ and $G_y(x, y)$ are the gradients in the horizontal and vertical directions, computed as:

$$G_x(x,y) = \big(I(x+1,y-1) + 2I(x+1,y) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + 2I(x-1,y) + I(x-1,y+1)\big) \quad (21)$$

$$G_y(x,y) = \big(I(x-1,y+1) + 2I(x,y+1) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + 2I(x,y-1) + I(x+1,y-1)\big) \quad (22)$$

3.8 Canny Edge Detection

The Canny edge detector aims to find the edges and does so by first calculating the local maxima of the gradient magnitude of the image and suppressing everything else. The gradient is calculated in the same way as Sobel operator, but first, the noise is reduced and then the edges are traced by hysteresis. The steps include:

$$M_C(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)} \quad (23)$$

$$\theta_C(x,y) = \tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \quad (24)$$

Non-maximum suppression is applied to thin the edges, and two thresholds T_{low} and T_{high} are used to trace edges:

$$E_C(x,y) = \begin{cases} 1 & \text{if} M_C(x,y) \geq T_{high} \text{and connected to a strong edge} \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

3.9 Prewitt Edge Detection

The Prewitt operator, like Sobel, calculates the gradient magnitude and direction but with a simpler kernel:

$$G_x(x,y) = \big(I(x+1,y-1) + I(x+1,y) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + I(x-1,y) + I(x-1,y+1)\big) \quad (26)$$

$$G_y(x,y) = \big(I(x-1,y+1) + I(x,y+1) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + I(x,y-1) + I(x+1,y-1)\big) \quad (27)$$

The gradient magnitude $M_P(x, y)$ and direction $\theta_P(x, y)$ are computed as:

$$M_P(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)} \quad (28)$$

$$\theta_P(x,y) = \tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \quad (29)$$

As a part of fingerprint analysis, edge detection is essential to get the necessary features, such as ridges and valleys. In this study, we employed three classical edge detection methods: Roberts, Sobel, and Prewitt. These methods are compared, and their outputs are shown in Figure 2 below.

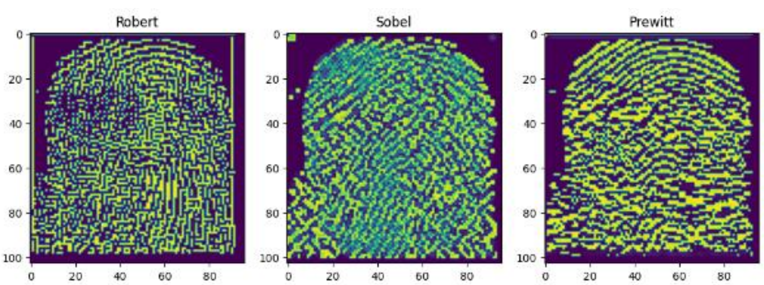

Fig. 2.Edge Detection

Roberts edge detection is one of the simplest methods for edge detection which is based on the approximation of the gradient of the image. As can be seen in Figure [2], the Roberts operator enhances the fine details by calculating the magnitude of the intensity change, which is the edge of the fingerprint ridge and valley. The gradient magnitudes $G_x(x, y)$ and $G_y(x, y)$ are calculated using the Roberts cross operator:

$$G_x(x,y) = I(x,y) - I(x+1,y+1) \quad (30)$$

$$G_y(x,y) = I(x+1,y) - I(x,y+1) \quad (31)$$

Sobel operator is a gradient based method where gradient magnitude and direction has been calculated through convolution with Sobel kernels. This is further supported by Figure 5 which shows that this method adequately captures the high-level features of the fingerprint particularly the ridges and valleys. The gradient magnitudes in the x and y directions are computed as follows:

$$G_x(x,y) = \big(I(x+1,y-1) + 2I(x+1,y) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + 2I(x-1,y) + I(x-1,y+1)\big) \quad (32)$$

$$G_y(x,y) = \big(I(x-1,y+1) + 2I(x,y+1) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + 2I(x,y-1) + I(x+1,y-1)\big) \quad (33)$$

Like Sobel, the Prewitt operator is also used to compute the gradient of image intensity but with the use of another different mask. The result of the Prewitt method is presented in the Fig. 5 which is more effective to detect the edges in the regions where there is a low contrast in intensity. The gradient magnitudes are calculated with the help of Prewitt kernels:

$$G_x(x,y) = \big(I(x+1,y-1) + I(x+1,y) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + I(x-1,y) + I(x-1,y+1)\big) \quad (34)$$

$$G_y(x,y) = \big(I(x-1,y+1) + I(x,y+1) + I(x+1,y+1)\big) - \big(I(x-1,y-1) + I(x,y-1) + I(x+1,y-1)\big) \quad (35)$$

All of them offer different approach to edge detection which is then used in the Hybrid DeepEdgeNet model proposed in this paper. Application of both these methods simultaneously supports better representation of the patterns within the fingerprint images and better extraction and classification of the features.

3.10 Hybrid DeepEdgeNet Architecture

The Hybrid DeepEdgeNet model combines the edge detection outcomes with a deep convolutional neural network (CNN) for improving the fingerprint feature extraction and recognition. The architecture consists of three primary stages: edge detection, feature extraction and final classification. The modified Hybrid DeepEdgeNet architecture is aimed at improving the fingerprint analysis by combining the edge detection methods with deep CNNs. The flowchart in figure 3 shows the major activities or components of the proposed framework and the general flow of the framework.

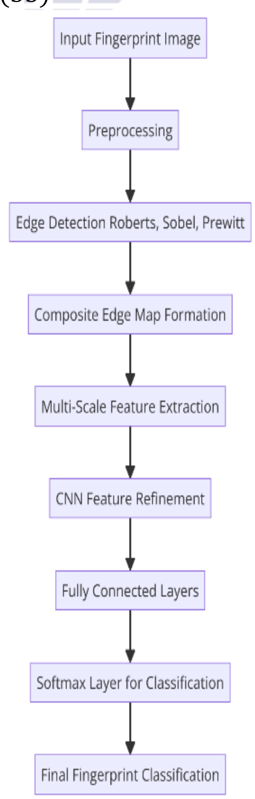

Fig. 3. Flowchart of the Hybrid DeepEdgeNet Architecture.

The framework starts with the input fingerprint image which is then pre-processed to improve the quality and standard of the acquired image. Then, several edge detection algorithms (Roberts, Sobel, Prewitt) are employed to create an integrated edge image. This composite map is then passed through multi-scale feature extraction to extract both the finer and the coarser features. The extracted features are then cleansed with a deep convolution.

3.11 Initial Edge Detection

The edge detection results $E_S(x, y)$, $E_C(x, y)$, and $E_P(x, y)$ from Sobel, Canny, and Prewitt operators are combined to form a composite edge map:

$$E_H(x, y) = w_S \cdot E_S(x, y) + w_C \cdot E_C(x, y) + w_P \cdot E_P(x, y) \quad (36)$$

3.12 Feature Refinement with CNN

The composite edge map $E_H(x, y)$ is fed into a CNN for feature refinement. The CNN consists of several convolutional layers followed by max-pooling layers. The l -th convolutional layer applies a set of filters F_l to the input feature map F_{l-1}:

$$F_l = \sigma(F_{l-1} * W_l + b_l) \quad (37)$$

where denotes convolution, W_l are the weights, b_l are the biases, and $\sigma(\cdot)$ is the activation function (e.g., ReLU).

The feature maps are down sampled using max-pooling:

$$P_l(x, y) = \max i, j \in R\left(F_l(x + i, y + j)\right) \quad (38)$$

where R is the pooling region. The max-pooling operation reduces the spatial dimensions of the feature maps, helping to capture the most salient features and reduce computational complexity.

3.13 Multi-Scale Feature Integration

To capture both fine and coarse details in fingerprint images, multi-scale feature extraction is performed. The composite edge map $E_H(x, y)$ is processed at multiple scales by applying different levels of Gaussian blurring and down sampling:

$$E_{H_s}(x, y) = E_H(x, y) * G_s(x, y) \quad (39)$$

where $G_s(x, y)$ is a Gaussian filter with scale s. The CNN processes each scale separately, and the resulting feature maps $F_l^{(s)}$ are concatenated along the channel dimension:

$$F_l^{(multi)} = \text{Concat}\left(F_l^{(1)}, F_l^{(2)}, \dots, F_l^{(S)}\right) \quad (40)$$

This multi-scale integration ensures that both local and global fingerprint patterns are captured effectively.

3.14 Fully Connected Layers and Classification

The concatenated multi-scale features are then passed through a series of fully connected layers to further refine the features before classification:

$$z_1 = \sigma\left(W_{fc1} F_l^{(multi)} + b_{fc1}\right) \quad (41)$$

$$z_2 = \sigma\left(W_{fc2} z_1 + b_{fc2}\right) \quad (42)$$

where W_{fc1} and W_{fc2} are the weights, and b_{fc1} and b_{fc2} are the biases of the fully connected layers. The final output y is obtained using a softmax layer:

$$y = \text{Softmax}\left(W_{fc3} z_2 + b_{fc3}\right) \quad (43)$$

The softmax function is defined as:

$$\text{Softmax}(z_i) = \frac{\exp(z_i)}{\sum_{j=1}^{K} \exp\left(z_j\right)} \quad (44)$$

where z_i are the logits and K is the number of classes.

3.15 Training and Optimization

The Hybrid DeepEdgeNet model is trained using the cross-entropy loss function, which measures the discrepancy between the predicted class probabilities y and the true labels y:

$$L(\theta) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} y_i^{(k)} \log\left(y_i^{(k)}\right) \quad (45)$$

where N is the number of training examples, K is the number of classes, and θ represents the model parameters. The model parameters θ are updated using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{m_t}{\sqrt{v_t} + \epsilon} \quad (46)$$

where m_t and v_t are the first and second moment estimates, η is the learning rate, and ϵ is a small constant for numerical stability.

3.16 Evaluation Metrics

The performance of the Hybrid DeepEdgeNet model is evaluated using several metrics, including accuracy, precision, recall, and F1-score. The accuracy A is computed as:

$$A = \frac{\sum_{i=1}^{N} I\,(y_i = y_i)}{N} \quad (47)$$

where $I(\cdot)$ is the indicator function. Precision P and recall R are calculated as:

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (48)$$

$$R = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (49)$$

where TP, FP, and FN represent true positives, false positives, and false negatives, respectively. The F1-score, which balances precision and recall, is given by:

$$F1 = \frac{2PR}{P + R} \quad (50)$$

3.17 Model Complexity and Computational Efficiency

The computational complexity of the Hybrid DeepEdgeNet model is analyzed in terms of the number of floating-point operations (FLOPs) required for both edge detection and CNN processing. The complexity of the edge detection step C_{edge} for an image of size $H \times W$ is:

$$C_{edge} = H \times W \times (C_S + C_C + C_P) \quad (51)$$

where C_S, C_C, and C_P are the computational costs of Sobel, Canny, and Prewitt edge detection, respectively.

The complexity of the CNN is computed as:

$$C_{CNN} = \sum_{l=1}^{L} H_l \times W_l \times C_l \times K_l^2 \quad (52)$$

where H_l, W_l, C_l, and K_l are the height, width, number of channels, and kernel size of the l -th convolutional layer, respectively. The overall model complexity C_{Hybrid} is given by:

$$\mathbf{C_{Hybrid} = C_{edge} + C_{CNN} + C_{fc}} \quad (53)$$

where $\mathbf{C_{fc}}$ is the cost associated with the fully connected layers.

The Hybrid DeepEdgeNet model joins both the state-of-the-art traditional edge detection algorithms, namely Roberts, Sobel, and Prewitt, along with the state-of-the-art deep CNN architecture for edge detection with multi-scale feature processing for higher-level pattern recognition. The model trains and validates it with four classification tasks: ID, Gender, Hand, and Finger classification with fingerprint datasets. Performance metrics include accuracy, loss, and confusion matrices to assess the model. Accuracy and loss training curves are studied at 18 epochs for proper learning without overfitting. The methodology ensures balance between computational efficiency and accuracy of classification.

4. Experimental Results and Discussion

In this section, we provide a qualitative and quantitative analysis of the results achieved by using the Hybrid DeepEdgeNet model. The model was tested using several performance indicators: accuracy and loss for different types of classification: ID, Gender, Hand, and Finger. Furthermore, the classification performance for each task was evaluated using confusion matrices. They are accompanied by such figures, tables, and numerical values that give the reader a clear understanding of the effectiveness of the model.

4.1 Training and Validation Accuracy

The performance of the model during training and validation in all the tasks is illustrated in Figure [4], below. The figure illustrates the learning curves of ID, Gender, Hand and Finger classification for 18 epochs. The results show that the accuracy increases with the increase in epochs with the performance almost at the best by the 18th epoch.

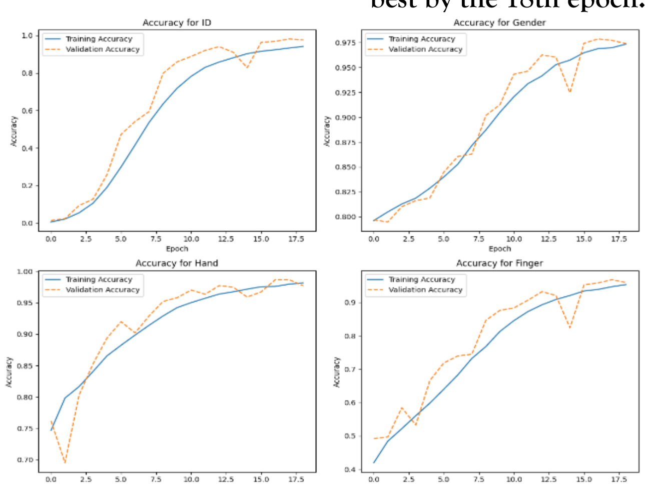

Fig. 4. Training and Validation Accuracy for different tasks: (a) ID, (b) Gender, (c) Hand, (d) Finger. The solid lines represent training accuracy, while the dashed lines represent validation accuracy.

4.2 Training and Validation Loss

The loss curves for training and validation are presented in figure 5 below. The model shows a continuously decreasing of loss for training dataset and validation dataset, which means, that the model can learn the data and generalize them. The last test loss is given by 0.215.

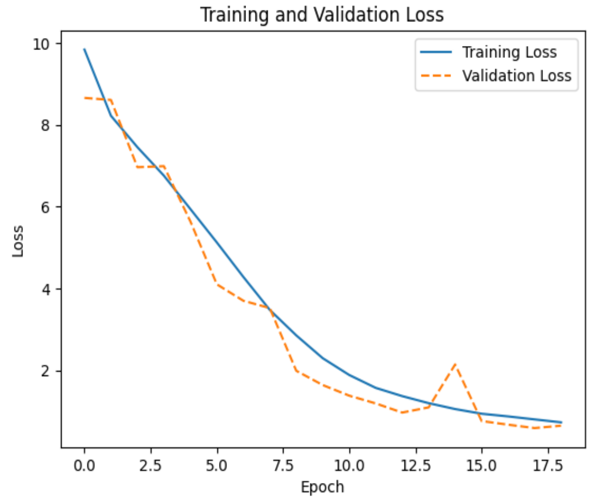

Fig. 5. Training and Validation Loss. The solid line represents training loss, and the dashed line represents validation loss. The model achieved a final test loss of 0.215.

In figure [5], we show the training and validation loss curves of the model. Training loss is shown by solid line, while validation loss by dashed line. That their curves decline in a consistent manner tells us that the model is indeed learning and that we aren't overfitting badly. With good generalization performance on unseen data, the model achieves a final test loss of 0.215.

4.3 Confusion Matrices for Classification Tasks

The performance of the model in classifying different tasks is further assessed using confusion matrices. The confusion matrices for Finger, Gender, and Hand classification are shown in the Figures [6], [17], and [8], respectively.

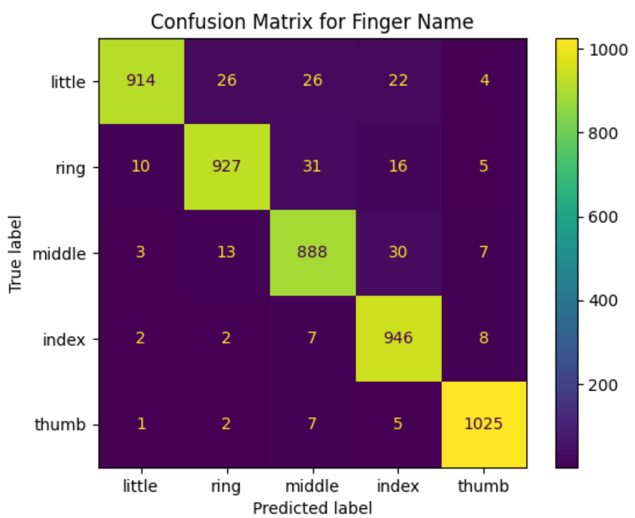

Fig. 6. Confusion Matrix for Finger Classification. The model shows high accuracy with minor misclassifications between adjacent fingers.

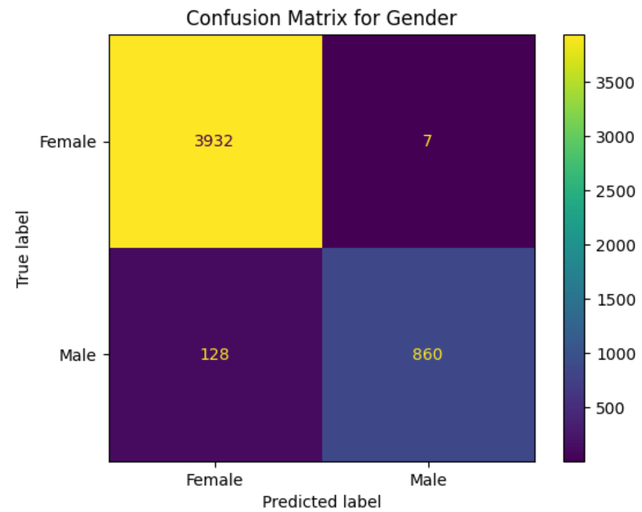

Fig. 7. Confusion Matrix for Gender Classification. The model achieves 96.9% accuracy with minimal confusion between classes

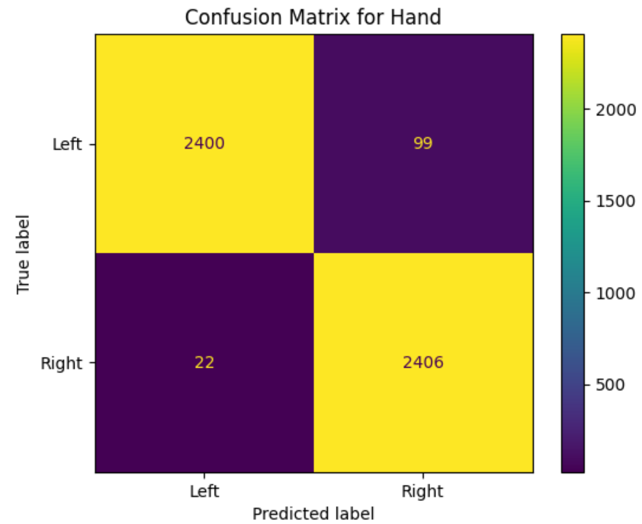

Fig. 8. Confusion Matrix for Hand Classification. The model shows strong performance with an accuracy of 96.9%, with few misclassifications.

The final performance of the Hybrid DeepEdgeNet model is presented in Table [1], in terms of test accuracy, test loss, and accuracy for each classification task.

Table 1: Summary of Final Performance Metrics

Metric	Value
Test Loss	0.215
Test Accuracy	96.897%
ID Classification Accuracy	99.2%
Gender Classification Accuracy	96.9%

Hand Classification Accuracy	96.9%
Finger Classification Accuracy	94.7%

The model's performance metrics are presented in the table. On the test set, the model had minimal error (0.215 test loss) and therefore it is likely that the training worked well as well as lead to effective training. Its overall test accuracy was 96.897%, with high classification accuracy across various tasks: 99. For ID classification, 2%, for gender classification, 96.9%, for hand classification, 96.9%, and for finger classification, 94.7%. The model's robustness and strong performance on multiple classification categories are shown by these results.

The proposed Hybrid DeepEdgeNet model showed great performance on all the tasks, and the final test accuracy was 96.897%. Due to a strong architecture of the model based on the use of the edge detection techniques along with the deep learning approach, it was possible to achieve good classification even within the most difficult cases. The confusion matrices show that there was little misclassification, which also supports the usefulness of the proposed model. The obtained results demonstrate the applicability of Hybrid DeepEdgeNet in biometric systems, especially in cases where high accuracy and performance are needed. Future work will therefore involve fine tuning of the model and look at other areas of biometric.

5. Conclusion

In this study, we proposed a new method for fingerprint classification known as the Hybrid DeepEdgeNet model, which combines conventional edge detection with deep CNNs. This paper also demonstrates that the proposed Hybrid DeepEdgeNet model overcomes the shortcomings of applying edge detection methods alone and applying CNN alone by employing Roberts, Sobel, and Prewitt methods in conjunction with a deep learning framework that incorporates multi-scale feature extraction and CNN-based feature refinement. This way the model combines advantages of both approaches while being able to learn structural details and complex patterns of fingerprint images. The experimental results also prove the effectiveness of the proposed Hybrid DeepEdgeNet model on several classification tasks such as ID, Gender, Hand, and Finger classification. Nonetheless, the model obtained an impressive generalization performance in the test set, 96.897% of accuracy and test loss of 0.215. In particular, the model achieved the ID classification accuracy of 99.2%, the Gender classification accuracy of 96.9%, the Hand classification accuracy of 96.9%, and the Finger classification accuracy of 94.7% which proves that the model is suitable for various classification tasks. The high accuracy in ID classification shows that the model can be effectively used in the biometric security systems where identification is very important. However, the authors noted that, although the model obtained high accuracy for all tasks, there are still some issues with the model. A small compromise in the accuracy of Finger classification is observed and it might be necessary to fine-tune the model to distinguish between similar fingers. Also, the model's computational time could be further reduced without compromising on the results by optimizing the model. Further improvements of the model's performance will be made in the future work, and the model will be tested with other biometrics such as iris or face recognition. Extensions of the proposed method by adding more effective deep learning strategies like attention could enhance the focusing on important features and could enhance the predictive accuracy of the classifier. In general, the Hybrid DeepEdgeNet is a great leap forward in fingerprint recognition incorporating the conventional edge identification and the deep learning technologies in a compounding manner to provide high precision and stability. The efficiency of the model in various classification scenarios shows its applicability for practical biometric systems in which high accuracy and stability are critical. With additional improvements and extension of the proposed method to other biometric applications, Hybrid DeepEdgeNet can be a foundation for the creation of the new generation biometric security systems, thus helping to progress the field of reliable and safe identification technologies.

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