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Smartphone-based fingerprint authentication using siamese neural networks with ridge flow attention mechanism

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ABSTRACT

Authenticating finger photo images captured using a smartphone camera provides a good alternative solution in place of the traditional method-based sensors. This paper introduces a novel approach to enhancing fingerprint authentication by leveraging images captured via a mobile camera. The method employs a siamese neural network (SNN) combined with a ridge flow attention mechanism and convolutional neural networks (CNN). Our approach begins with collecting a dataset consisting of finger images from two individuals then we apply multiple preprocessing techniques to extract fingerprint images, followed by generating augmented data to improve model robustness, scaling, and normalizing them to form images suitable for model training. Next, we generate positive and negative pairs for training a SNN. We used the SNN with CNN for feature extraction, combined with an attention mechanism that focuses on the ridge flow pattern of fingerprints to improve feature relevance which significantly contributed to the performance enhancement. As for the testing performance, our model has an accuracy of 90%, precision of 89%, recall of 83%, F1 score of 86%, area under the curve (AUC) 95 %, and 13% of equal error rate (EER) when using smartphone-captured images for fingerprint recognition.

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1. INTRODUCTION

Biometric authentication has gained significant attention in recent years, with fingerprint recognition being one of the most widely adopted methods due to its reliability, uniqueness, and ease of use. Traditional fingerprint recognition systems rely on physical contact with dedicated sensors to capture high-resolution fingerprint scans for precise feature extraction and matching [1], [2]. However, these systems present several challenges, including sensor wear and tear, hygiene concerns, and user inconvenience [3], [4]. With the growing prevalence of smartphones, there is increasing interest in developing contactless fingerprint recognition systems that utilize mobile cameras, offering a non-invasive and user-friendly alternative [5], [6].

Contactless fingerprint recognition leverages high-resolution cameras to capture detailed ridge structures without requiring physical contact [7], [8]. While this approach offers several advantages, such as improved hygiene and ease of use, it also introduces significant challenges. Variations in lighting, finger pose, and background noise can degrade image quality, making it difficult to extract discriminative features such as ridge patterns and minutiae. These issues are further exacerbated in real-world conditions, where smartphone-based systems must operate efficiently on resource-constrained devices.

Recent research has made considerable progress in improving contactless fingerprint recognition. Alkhathami *et al.* [9] introduced a touchless approach using multiple mobile camera images combined with the mosaic method to enhance the usable fingerprint area. Sankaran *et al.* [10] developed a fingerphoto matching technique using ScatNet features and created a public database to address environmental and background challenges. Genovese *et al.* [11] explored the use of Level 3 features, such as sweat pores, for touchless fingerprint recognition using neural networks. Further advancements include the monogenic-wavelet algorithm for improved accuracy in smartphone-based systems by Birajadar *et al.* [12], convolutional neural networks (CNN) based classification optimization for low-quality fingerprints by Lăzărescu *et al.* [13], and a siamese neural network (SNN) for fingerphoto verification introduced by Singh *et al.* [14]. More recently, Ramachandra and Li [15] proposed Finger-NestNet, incorporating a nested residual block architecture to achieve superior verification accuracy.

Despite these advancements, challenges remain, particularly in improving robustness to noise, ensuring real-time performance on mobile devices, and extracting reliable features under varying conditions. Many existing methods struggle with maintaining accuracy in uncontrolled environments where variations in lighting and finger positioning significantly impact recognition performance. Additionally, while deep learning techniques have shown promise, their computational demands often limit their deployment on resource-constrained devices.

To address these challenges, this paper proposes a novel deep-learning framework that integrates SNN architecture with a CNN base network enhanced by a ridge flow attention mechanism. The SNN is well-suited for one-shot learning tasks such as fingerprint matching, while the CNN base network, equipped with ridge flow attention mechanism, focuses on extracting robust and discriminative features, even from low-quality images. A custom dataset of fingerprint images was collected using our smartphones, capturing variations in lighting, finger pose, and background conditions to ensure a realistic assessment. The framework is optimized for efficiency using model pruning and quantization to enable real-time performance on mobile devices. By improving feature extraction, enhancing robustness to environmental variations, and optimizing computational efficiency, this research contributes to advancing the accuracy and practicality of contactless fingerprint recognition systems for mobile applications.

2. METHOD

This section presents the proposed methodology, as illustrated in Figure 1. The framework consists of four main stages: dataset collection, fingerprint extraction process, feature extraction utilizing a siamese network-based architecture for fingerprint photo verification, and classification followed by evaluation. Each stage is elaborated in detail in the following subsections.

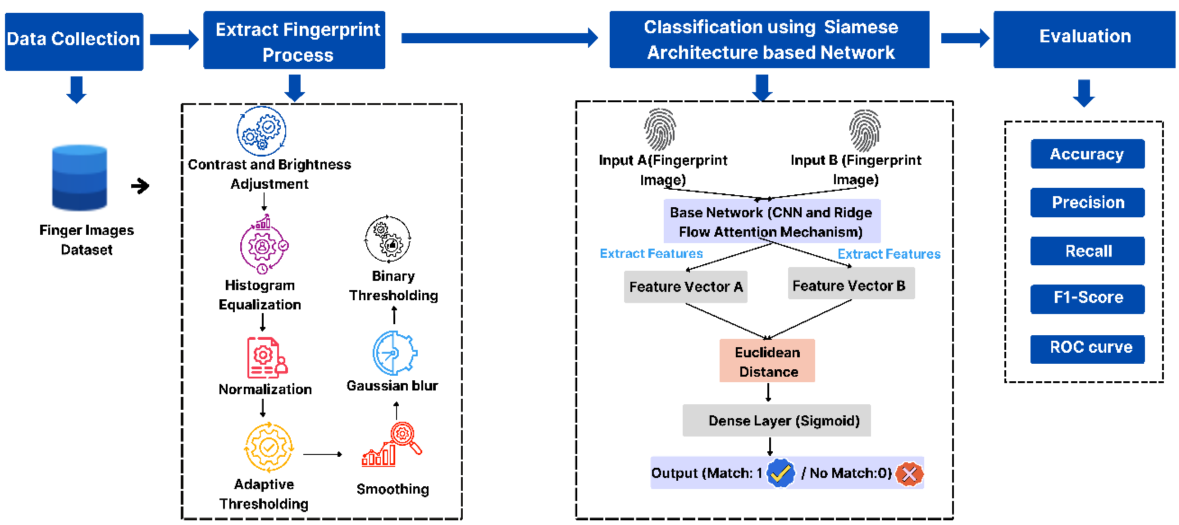

Figure 1. The proposed approach

2.1. Dataset collection

In this section, we describe the data collection and augmentation process for our study. Finger images were captured from two individuals using a smartphone camera, with each participant providing ten (10) images of the same finger under consistent lighting conditions to ensure clarity and visibility. During the capture process, only the section containing the fingerprint was selected, rather than the entire finger. Given the limited size of the dataset, we employed ImageDataGenerator to perform data augmentation, applying transformations such as rotations, shifts, shears, zooms and flips [16]. For each original image, five augmented versions were generated to expand the dataset and enhance the model's performance. Figure 2 illustrate the data collection and augmentation process.

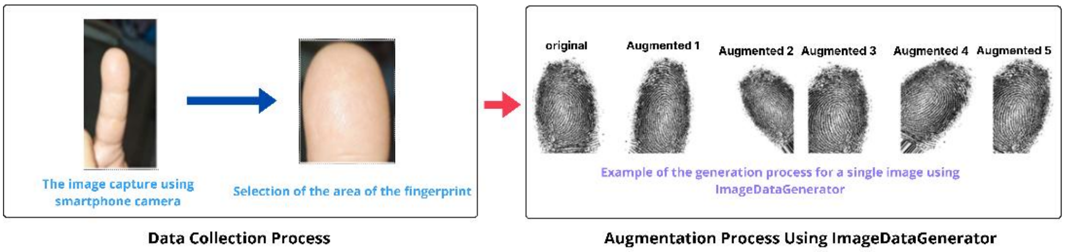

Figure 2. Data collection and augmentation process for fingerprint

2.2. Extract fingerprint

The process starts by detecting the finger and masking the background based on contour detection, followed by several image enhancement techniques. The contrast and brightness of the image are adjusted through histogram equalization for better intensity distribution. The subsequent preprocessing steps include the normalization of pixel values, making the image ready for adaptive thresholding. Adaptive thresholding is used to binarize the image based on local variations in light intensity, followed by smoothing with a median filter and Gaussian blur to reduce noise. Lastly, the image undergoes binary thresholding to create a clean image that making the fingerprint features more pronounced for further processing [5], [10]. Figure 3 illustrates the sequential steps involved in extracting fingerprints from the images captured via a mobile camera to improve the features of fingerprints.

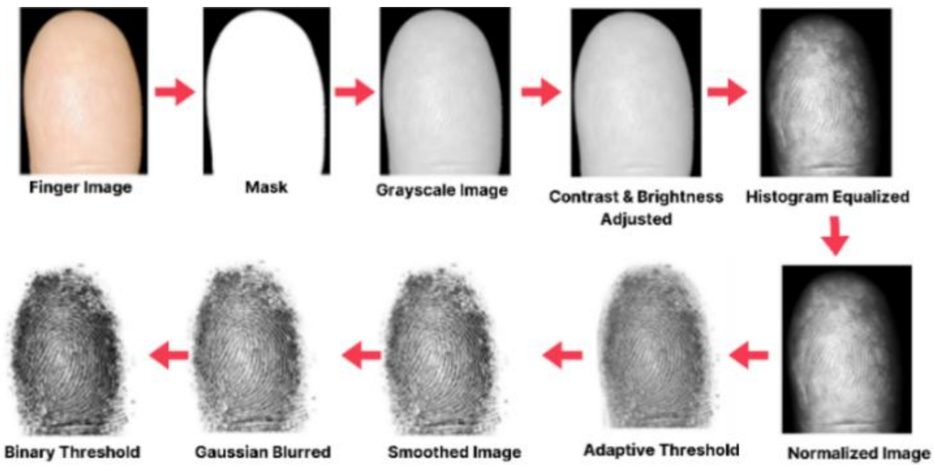

Figure 3. Extracting fingerprint steps

2.2.1. Contrast and brightness adjustment

The transformation for adjusting the contrast and brightness of the image can be described by the (1) [17], [18].

$$I' = \alpha \, . I + \beta \tag{1}$$

Where I is the original pixel intensity (grayscale value) of the image, I′ is the new pixel intensity after adjustment, α is the contrast factor and β is the brightness offset. This linear transformation adjusts the image globally by scaling the intensity values and shifting them.

2.2.2. Histogram equalization

Histogram equalization redistributes the intensities to enhance the global contrast of the image [18]. The transformation is based on the cumulative distribution function (CDF) of the image's histogram as defined in the (2).

$$I'\,(x,y) = (CDF(I(x,y)) - CDFmin)/(N-1) \times 255 \tag{2}$$

Where $I(x,\ y)$ is the original intensity value at pixel location (x, y), $I'(x,\ y)$ is the new intensity after equalization, CDF(I$(x,\ y)$ is the cumulative distribution function for intensity $I(x,\ y)$, CDFmin is the minimum value of the CDF and N is the total number of pixels.

2.2.3. Normalization

Normalization scales the pixel intensities to a specific range, typically [0, 255], using the (3) [18], [19].

$$I' = \frac{I-Imin}{Imax-Imin} \times 255 \tag{3}$$

Where Imin and Imax are the minimum and maximum pixel values in the image I and I' is the normalized pixel intensity.

2.2.4. Adaptive gaussian thresholding

Adaptive thresholding computes a threshold based on the local mean of pixel intensities in a window around each pixel as defined in the (4) [20].

$$T(x,y) = \mu(x,y) - C \tag{4}$$

Where T(x, y) is the threshold at pixel (x, y), μ(x,y) is the weighted sum of pixel intensities within the local window around $(x,\ y)$, computed using a Gaussian function and C is a constant subtracted from the mean to control threshold sensitivity.

2.2.5. Smoothing (median and gaussian blur)

Median filtering replaces each pixel's value with the median value of the surrounding pixels in a window, as defined in (5) [21].

$$I'(x,y) = median\{\, I(\mu,\vartheta)\ |\ (\mu,\vartheta)\ \in\ W(x,y)\} \tag{5}$$

Where W(x,y) is a window centered at pixel (x,y). Gaussian blur smooths the image by convolving it with a gaussian kernel as defined in (6).

$$I'(x,y) = \sum_{\mu,\vartheta} G(\mu,\vartheta)\,.\,I(x-\mu\,,y-\vartheta) \tag{6}$$

Where G(u,v) is the Gaussian kernel and I(x,y) is the pixel value at position (x,y).

2.2.6. Binary thresholding

The binary thresholding operation converts the image into a binary form by applying a global threshold as defined in (7) [22].

$$I'(x,y) = \begin{cases} 255 & if\ I(x,y) > T \\ 0 & Otherwise \end{cases} \tag{7}$$

Where T is a predefined threshold value, typically set manually or experimentally.

2.3. Image preprocessing

The process prepares fingerprint images for input into the base network of the Siamese network by resizing them to a consistent dimension 128×128 pixels and normalizing pixel values to a range of 0 to 1. This standardization ensures uniform processing and stable learning. Figure 4 shows an example of a processed image.

2.4. Generating pairs for siamese networks

Making pairs involves creating two distinct sets of inputs that either belong to the same class (positive pairs) or different classes (negative pairs), with the network trained to distinguish between them by computing a similarity measure. Positive pairs consist of images from the same class, such as two images of the same person's finger, while negative pairs consist of images from different classes, such as two images of different individuals' fingers.

Figure 4. Preprocessed image

2.5. CNN base network with ridge flow attention mechanism

The base network of the Siamese model is designed to effectively extract and compare fingerprint features. It begins with three convolutional layers (Conv2D) with increasing filter sizes (32, 64, 128), allowing the network to capture progressively complex patterns from the input images. Each convolutional layer is followed by a MaxPooling2D layer, which reduces spatial dimensions while preserving essential fingerprint features. To enhance the network's ability to focus on fingerprint ridge patterns, a ridge flow attention mechanism is incorporated. This mechanism consists of additional Conv2D layers that compute attention weights, which are then applied to the input features to emphasize relevant details. The extracted features are then flattened and passed through two fully connected layers with 256 and 128 units, enabling the model to learn high-level representations. This architecture ensures robust and discriminative feature extraction for fingerprint matching. Figure 5 illustrates the structure of the base network within the siamese model, highlighting the integration of CNN layers and the ridge flow attention mechanism.

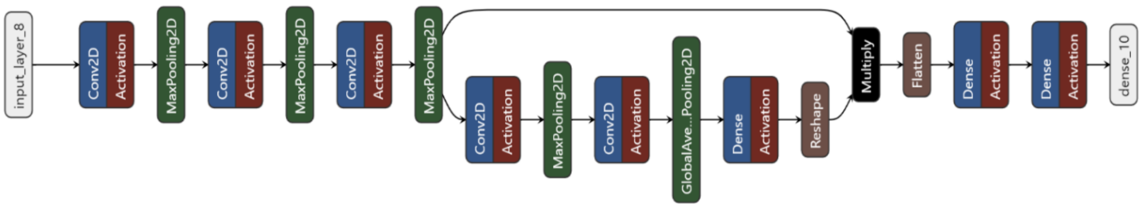

Figure 5. Model architecture of CNN with ridge flow attention mechanism

2.6. Siamese network architecture

The proposed method employs a siamese network to compare fingerprint image pairs and determine if they belong to the same individual. Each input image is processed through a CNN-based base network, which integrates a ridge flow attention mechanism to enhance crucial features. The absolute difference between the outputs of the base network for the two images is then computed, and a dense layer classifies the images based on this difference. Figure 6 illustrates the overall architecture of the siamese network.

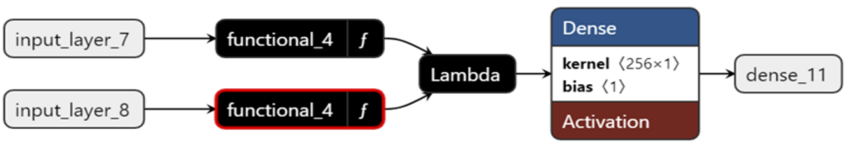

Figure 6. Siamese network architecture

2.7. Training and evaluation

In this section, we describe the training and evaluation process of our model, designed to distinguish between fingerprints from different individuals. We generate pairs of fingerprint images, assigning labels 0 for negative pairs (images from different individuals) and 1 for positive pairs (images from the same individual). The dataset is divided into training and test sets, and the model is trained on the generated pairs. The evaluation phase assesses the model's performance in accurately classifying fingerprint pairs, ensuring robustness and reliability in distinguishing between individuals. To evaluate the performance of the classification system, several metrics were employed including accuracy, precision, recall and F1-score.

Accuracy measures the proportion of correctly classified instances out of the total number of cases [23]. It is calculated by the (8).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

Precision which quantifies the accuracy of positive predictions, indicating how many of the predicted positive cases are actually true positives [23]. It is computed by the (9).

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

Recall also known as sensitivity, it measures the proportion of actual positive cases that are correctly identified by the model [23]. It is calculated by the (10).

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

F1-score is the harmonic mean of precision and recall, providing a balanced measure between the two metrics. It is particularly useful when dealing with imbalanced datasets [23]. The formula for F1-score is illustrated in the (11).

$$\mathrm{F1-Score} = 2 \times \frac{Precison \times Recall}{Precison \times Recall} \tag{11}$$

In addition to these metrics, the receiver operating characteristic (ROC) curve is a graphical representation of a binary classifier's performance across various threshold settings. It plots the true positive rate (TPR) against the false positive rate (FPR) to illustrate the trade-off between sensitivity and specificity. The area under the ROC curve (AUC) is a scalar value ranging from 0 to 1, where a higher AUC indicates better discriminative ability of the model. A perfect classifier has an AUC of 1, while a random classifier has an AUC of 0.5 [24].

Another important metric for biometric systems is the equal error rate (EER). The EER is the point where the false acceptance rate (FAR) and false rejection rate (FRR) are equal. It is a critical metric for biometric systems, as it represents the error rate at which the system achieves an optimal balance between FAR and FRR. A lower EER indicates better system performance [25].

3. RESULTS AND DISCUSSION

Our proposed approach, which combines fingerprint extraction from images taken with a mobile camera and trains a SNN using Keras and TensorFlow, achieved promising results in fingerprint recognition. The performance metrics reported 90% accuracy, 83% recall, 86% F1 score, and 89% precision indicating the model's effective ability to identify and match fingerprints, demonstrating good capacity for fingerprint recognition tasks. Table 1 presents a classification report summarizing these metrics for each class.

Table 1. Classification report

	Precision	Recall	F1-score
0	0.91	0.94	0.92
1	0.89	0.83	0.86

Figure 7 illustrates the performance metrics of the Siamese network used for fingerprint image classification, highlighting trends in accuracy and loss during training. Both training and test dataset accuracy increase progressively with the number of epochs, demonstrating the network's ability to effectively learn and distinguish between fingerprint pairs. Concurrently, the loss for both datasets decreases, indicating a reduction in prediction errors and improved model performance. These results emphasize the Siamese network's capability to extract and compare meaningful features from fingerprint images, enabling accurate classification.

Figure 8 presents the ROC curve of our model, along with the calculated AUC and EER values. The model achieves an AUC of approximately 95%, demonstrating its effectiveness in minimizing false positives and maximizing true positives across various thresholds. Additionally, it attains an EER of 13%, reflecting a balanced trade-off between false acceptances and false rejections. These results underscore the model's strong classification performance.

To test the model's generalization, new fingerprint images from person one and person two were processed using a pre-trained siamese network. A similarity threshold of 0.5 was used to determine if the images belonged to the same person. Figure 9 shows three cases: (1) two images of the same finger from person 1 scored 0.67, (2) two images of the same finger from person 2 scored 0.81, and (3) images from different individuals scored 0.12. These results confirm the model's ability to accurately distinguish between fingerprints of the same and different individuals.

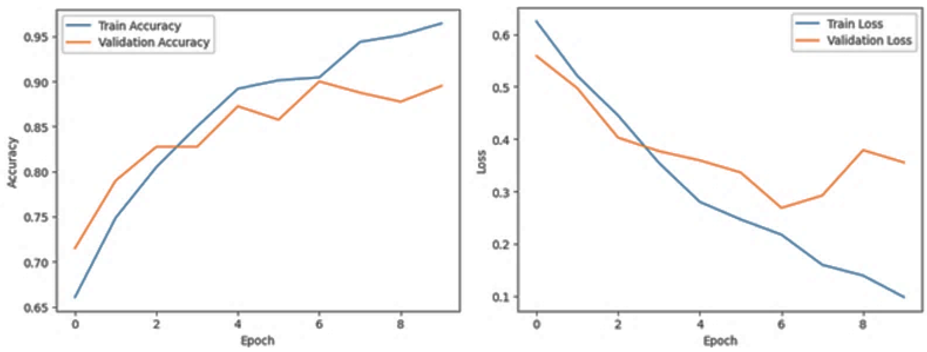

Figure 7. Graph accuracy and loss

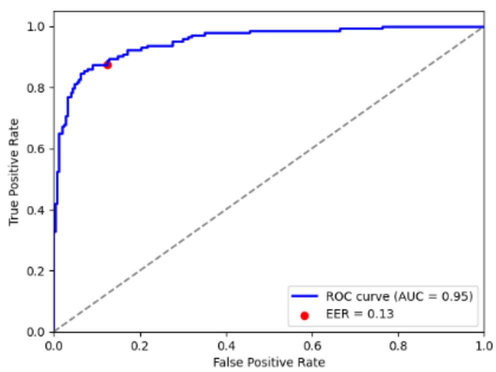

Figure 8. ROC curve

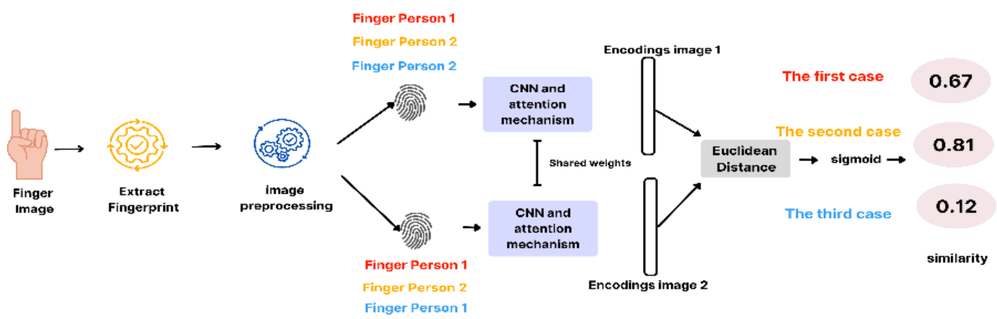

Figure 9. Evaluation of similarity scores for fingerprint classification

As a simple comparison with similar works mentioned in the introduction to this research, our approach demonstrates competitive performance in fingerprint recognition using smartphone-captured images. The study in [13], which utilized a CNN, reported 70.2% and 75.6% test accuracy. In contrast, our approach achieved an accuracy of 90%, substantially outperforming the results reported in [13]. However, our EER of 13% is higher than the 1.15% reported in [15], which employed a ResNet-based model for fingerphoto verification, indicating that [15] achieves superior performance in terms of error rate. On the other hand, our EER is lower than the 8.9% to 34.7% range reported in [14], which used a siamese network for comparing inputs, suggesting that our model performs better than theirs regarding error rate.

Overall, our study demonstrates the potential of smartphone-based fingerprint recognition and lays the foundation for more robust and scalable biometric authentication systems, contributing to the field's advancement and practical applications. Table 2 provides a comparison of our research with existing works, detailing the datasets used, the methodologies applied, the models employed, and the evaluation metrics achieved. This comparison helps to contextualize our results within the broader landscape of related research.

Table 2. Comparison between state-of-the-art finger photo recognition methods with our work

Reference	Methodology	Device capturing	Dataset	Techniques	Metrics
[9]	This approach captures multiple views of the fingerprint and stitches these images together into a single mosaic that represents the entire fingerprint. The stitching process involves aligning and combining images from different angles to create a coherent and detailed fingerprint image.	Mobile camera without flash	Custom dataset	Minutia SIFT	Minutia accuracy 97% SIFT accuracy 97.5%
[10]	This paper uses traditional image processing techniques and texture analysis to extract features from fingerphotos	Mobile camera, optical sensor without flash	Custom dataset	Neural network and random decision forest (RDF)	EER = 3.56%
[11]	The system captures high-resolution touchless images and focuses on extracting detailed pore-level features from fingerprints, which are processed using neural networks for classification and matching.	Digital camera	Custom dataset	KNN-1 KNN-3 Naive Bayes FFNN-30	76.0% 79.2% 71.9% 83.4%
[12]	The system captures high-resolution images of fingerprints from different angles and uses feature extraction techniques to compare these with stored fingerprint data	Smartphone With flash	fingerprint dataset prepared by Indian Institute of Technology Bombay, Mumbai, India	monogenic-wavelet algorithm	/
[13]	hybrid approach combining traditional edge detection with deep learning (CNNs) for fingerprint matching	DB1: optical sensor "V300" by CrossMatch DB2: optical sensor "U.are.U 4000" by Digital Persona DB3: thermal sweeping sensor "FingerChip FCD4B14CB" by Atmel DB4: synthetic fingerprint generation	FVC2004, DB1, DB2, DB3, and DB4 datasets	CNN	Accuracy (67.6% to 98.7%) for the validation set, and (70.2% to 75.6%) for the test set
[14]	They used Siamese network for comparing two inputs to determine their similarity	Smartphone	Public dataset	Siamese network CNN	EER ranging from 8.9% to 34.7%
[15]	developing a deep learning-based model (possibly a version of ResNet) that can verify fingerphotos	The rear camera of the iPhone6 Smartphone	Finger photo dataset	ResNet	EER = 1.15%.
Our work	Extract finger pring from finerphoto then using	Mobile camera with flash	Custom dataset	Siamese network CNN and ridge flow attention mechanism	Accuracy: 90% EER = 13%.

4. CONCLUSION

In recent years, touchless fingerprint recognition using smartphone-captured images has gained significant attention due to its convenience and hygiene advantages. This study introduced a novel approach to fingerprint authentication by leveraging a Siamese network integrated with a CNN and a ridge flow attention mechanism. Our method focuses on extracting and enhancing fingerprint features from fingerphotos, achieving an accuracy of 90% and an EER of 13%. These results demonstrate the effectiveness of our approach, outperforming other machine learning techniques and highlighting its potential for practical use in biometric authentication systems. By enabling the model to focus on critical ridge patterns, the attention mechanism significantly improves feature relevance and interpretability, making the system more robust and reliable.

Our study has limitations, including a small dataset, computational complexity, and a precision-recall trade-off, which need addressing to improve robustness and scalability. Future work should focus on expanding the dataset, optimizing for real-time use, exploring hybrid models, and enhancing interpretability. These improvements will refine our approach, making it more practical for real-world applications. This work advances mobile-based biometric authentication, offering a secure and convenient solution with significant potential to enhance security and convenience in everyday applications.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This study does not involve human participants whose identity could be disclosed.

ETHICAL APPROVAL

The study does not involve human or animal subjects.

DATA AVAILABILITY

The dataset used in this study was created and compiled by the authors. It is not publicly available due to privacy and security considerations, but it can be made available by the corresponding author upon reasonable request.

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