Performance analysis on fingerprint identification by deep learning approach

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Abstract: Achieving high accuracy in fingerprint identification remains challenging, despite various approaches that have been introduced over the years, including deep learning-based methods. These approaches can be computationally complex and may require a vast amount of training data. This study aims to evaluate the performance of deep learning-based approaches for fingerprint identification using two pretrained deep network models, *i.e.*, GoogLeNet and ResNet18. The images in the datasets are first registered and cropped before being trained and validated. The validation rates demonstrated that the preprocessed images produced higher average validation rates compared to the original images. These images are then applied during the testing phase, resulting in nearly perfect identification rates for both models. In comparison, with only 20% of the training dataset, GoogLeNet and ResNet18 achieved 93.00% and 97.00% for the FingerDOS database, respectively. Both models obtained an 88.75% identification rate on the FVC2002 DB1A database, outperforming other methods.

Keywords: fingerprint identification; biometric; deep learning; GoogLeNet; ResNet18; image registration; speeded up robust features; SURF.

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1 Introduction

Fingerprint has been widely used as a trait in biometric identification due to its uniqueness and permanence. Traditional fingerprint identification techniques rely on the unique pattern of ridges and valleys present on the surface of the individual's fingers (Krish et al., 2019). These methods are generally classified as correlation-based, minutiae-based and ridge-based methods (Maltoni et al., 2022). Correlation-based methods cannot be used when the fingerprint image is transformed (Sreeja, 2023). Minutiae-based methods require extensive preprocessing and are not reliable when the image quality is poor (Socheat and Wang, 2020; Anandha Jothi and Palanisamy, 2022). Ridge-based, on the other hand, are preferred when image quality is low but combining them with minutiae-based methods increases computational complexity (Dyre and Sumathi, 2016). The accuracy of these methods heavily relies on the quality of the fingerprint sample, and various factors such as image resolution, sensor noise, and image distortion may significantly affect the identification performance (Valdes-Ramirez et al., 2019). Moreover, these traditional methods require appropriate algorithms to identify unique patterns of the fingerprint, which can be time-consuming and make accurate identification more challenging (Dincă Lăzărescu et al., 2022). These limitations suggest the need for more sophisticated methods that can improve both accuracy and efficiency in fingerprint identification.

Recently, deep learning approaches have shown great potential in improving the performance of fingerprint identification in which the performances are enhanced to achieve higher accuracy and robustness (Yoo et al., 2020; Ghafoor et al., 2021; Wu et al., 2021; Gona and Subramoniam, 2022). One of the major advantages of deep learning-based fingerprint identification compared to traditional methods is that it can handle large and complex datasets (Chiroma, 2021). Moreover, these methods can directly learn from raw data without the need for feature extraction, which can reduce the processing time and improve the overall performance (Dyre and Sumathi, 2016). Alrashidi et al. (2021) proposed a cross-matching system based on Siamese architecture for fingerprint verification and achieves comparable performance with other methods. Herbadji et al. (2022) used pretrained deep neural networks (DNNs) through transfer learning to improve contactless fingerprint recognition and demonstrated the capability of the proposed method in the recognition. Meanwhile, Saul et al. (2023) proposed a fingerprint identification system that combines convolutional neural network (CNN), softmax, and random forest (RF) classifiers to improve accuracy and performance. The method is evaluated on a public database and shows promising results. These studies, among others, demonstrate the potential of deep learning models for fingerprint identification tasks.

Deep convolutional neural network (DCNN) architecture like GoogLeNet (Szegedy et al., 2015) and ResNet (He et al., 2016) have demonstrated state-of-the-art performance in various image classification tasks, including fingerprint identification. They are initially designed to learn features from image data and classify the images into different categories. While both architectures have achieved state-of-the-art performance on various image classification tasks, they differ in terms of their design, computational efficiency and memory requirements. GooLeNet is designed to parallelise convolutional layers of different sizes that allows it to capture information at different scales. ResNet, on the other hand, uses residual connections to address the vanishing gradient in very deep networks. These networks have been extensively studied and benchmarked on large datasets, making them reliable and widely used baselines for performance evaluation in the field of deep learning-based fingerprint identification (Listyalina and Mustiadi, 2019; Shi et al., 2022). Table 1 summarises various fingerprint identification methods along with their respective test image databases and performance metrics. Methods range from traditional minutiae-based and correlation-based approaches to advanced deep learning techniques, with performance assessed using metrics such as accuracy, error rates, and matching scores across different datasets.

Table 1 Fingerprint identification methods and their performance metrics

Method	*Reference*	*Test images*	*Performance metrics*
Minutiae-based	Krish et al. (2019)	GCDB	Rank-1 identification
Correlation-based	Sreeja (2023)	FVC2004, internal, SOCOFing, SFinGe	EER, FMR, FNMR, accuracy, average recognition rate
Ridge-based	King et al. (2023)	Contactless fingerprints	Genuine score
Minutiae and ridge-based	Zong and Ning (2008)	FVC2004 DB1A	FRR, FAR
FinSNet	Yoo et al. (2020)	Tsinghua	FAR, TAR
CNN (SMV-CNN)	Ghafoor et al. (2021)	NIST-4 DB, FVC2002 DB1A, FVC2004	EER, FNMR, accuracy
DLCNN-based Gabor-IPCA	Gona and Subramoniam (2022)	FVC2002	Accuracy, sensitivity, specificity, FRR, FAR, FMR, FNMR
Siamese (cross-matching)	Alrashidi et al. (2021)	FingerPass, MOLF	EER, FMR, FNMR, accuracy, matching time
Pretrained DNN (transfer learning)	Herbadji et al. (2022)	PolyU	Accuracy
CNN, softmax, random forest	Saul et al. (2023)	SDUMLA-HMT	Accuracy
Frequency domain	Khazaal and Mahdi (2019)	FVC2004	Efficiency, average error rate

As deep learning approaches are rapidly being explored in many applications (Patra et al., 2022; Sallam et al., 2023), there is a need to study their capabilities and limitations in fingerprint identification. The accuracy of the identification system can be affected by a variety of factors, such as the variation of the fingerprint images and the size of the dataset used in the training. According to a survey on deep learning for biometric recognition (Mehraj and Mir, 2021), one disadvantage of deep learning-based method is that the model must be complex enough to handle image variations. While deep learning models are designed to handle such complexities, their effectiveness heavily depends on the availability of large amounts of data. Despite many reported successes, fingerprint identification systems continue to face challenges. Although there have been advancements in deep learning, research on how constrained training datasets impact overall performance, particularly in fingerprint identification, has been limited. Therefore, this study is justified by the need to explore how limited training datasets affect the performance of deep learning-based methods. By examining the application of transfer learning with pretrained models such as GoogLeNet and ResNet18, this study aims to evaluate the performance of pretrained deep networks in fingerprint identification. The impact of the training dataset size on the identification system's performance is analysed. In addition, the study investigates whether image preprocessing can enhance the model's ability to accurately identify fingerprints. This research offers a better understanding of the minimum amount of training data required for effective fingerprint identification using deep learning methods and addresses the capabilities and limitations of this approach.

The contributions of the proposed performance evaluation are threefold. Firstly, the study goes beyond the mere application of deep learning by specifically evaluating pretrained DCNN, namely GoogLeNet and ResNet18, for fingerprint identification. Secondly, in contrast to other evaluations of fingerprint identification systems, this study applies minimal image preprocessing techniques that reveal the true performance of the DCNN. Finally, an extensive performance evaluation is included that explains the connection between the depth of the DCNN architecture and the efficacy of the identification system. This investigation reveals that increased depth in architecture does not consistently result in better performance. While deep learning has proven successful in various computer vision tasks, its application to biometric recognition is an emerging field. By evaluating pretrained DCNNs, this study led to a wider opportunity for more efficient and accurate identification systems. Moreover, many studies often employ extensive image preprocessing to enhance model performance, but this can obscure the true capabilities and limitations of the deep learning models themselves. In this study, two experiments are conducted and compared: one without image preprocessing and the other with it. This approach provides a more transparent assessment of the DCNN's intrinsic performance in fingerprint identification.

2 Network architectures

GoogLeNet and ResNet18 are differ significantly in their designs and performance. This section describes the key differences between these two deep learning architectures.

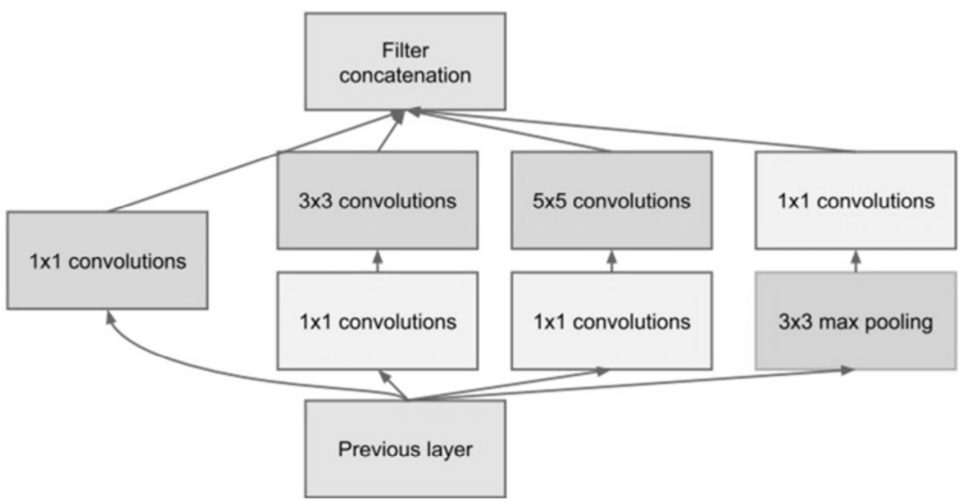
2.1 Network depth

In terms of network depth, GoogLeNet has a deeper network compared to ResNet18. GoogLeNet, with 22 layers, is designed based on the concept of inception modules. This design allows for efficient multi-scale feature extraction within the same layer by using filters of different sizes. On the other hand, ResNet18 contains only 18 layers, applying the concept of residual connections.

2.2 Architecture concepts

A key concept of the inception architecture in GoogLeNet is to determine an optimal local sparse structure in a convolutional vision network with readily available dense components (Szegedy et al., 2015). Figure 1 shows the inception module with dimension reductions in which the convolutions serve a dual-purpose, i.e., as reduction and rectified linear activation. To capture features from previous layers, the inception module is designed with 1 × 1, 3 × 3, and 5 × 5 convolutional kernels along with 3 × 3 max pooling. The network consists of stacked modules with occasional max-pooling layers. The lower layers of the GoogLeNet architecture still use the traditional convolutional network, while the higher layers utilise the inception modules.

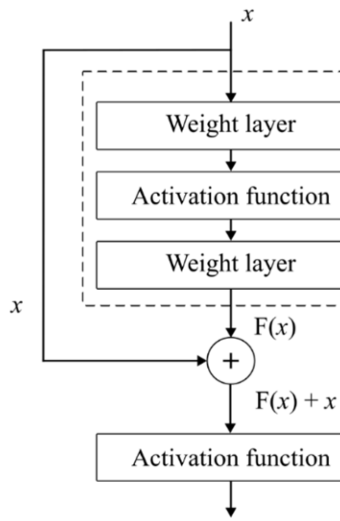
Figure 1 Inception module with dimension reductions



Source: Szegedy et al. (2015)

The ResNet architecture addresses the degradation problem in very DNNs through the use of residual connections. Figure 2 illustrates a basic building block of residual learning. Shortcut connections are used in the architecture in which one or more layers in the network are skipped. Consider a subnetwork consisting of a few consecutive layers, and let us denote the function performed by this subnetwork as $H(x)$, where x is the input to this subnetwork. With the concept of residual learning, the stacked nonlinear layers fit to another mapping of $F(x) := H(x) - x$. Thus, the output of this subnetwork can be expressed as $F(x) + x$. The shortcut connection allows the information from the previous layer to be propagated in the following layers.

Figure 2 Basic building block of residual learning



2.3 Complexity

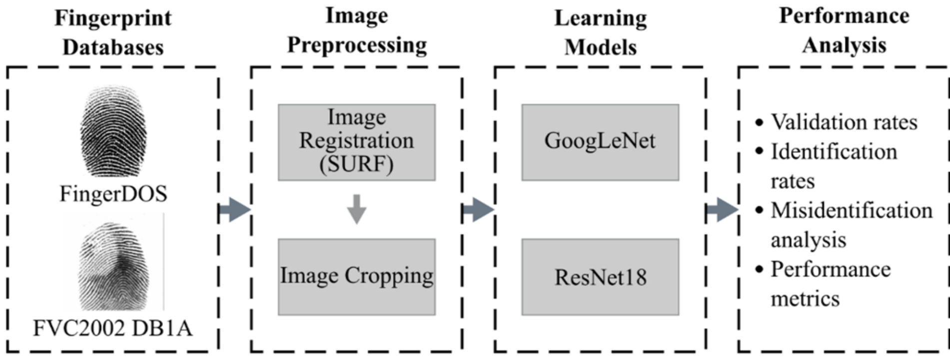
GoogLeNet is relatively deeper than ResNet18, which theoretically makes it computationally more expensive during training. According to Szegedy et al. (2015), the inception architecture utilises the dimension reduction capabilities to minimise the computational complexity increment when the number of units at each stage is increased. However, it was later claimed that this architecture has limitations and complexity that remain unexplained (Balagourouchetty et al., 2020).

ResNet18, on the other hand, has a good balance between model complexity and performance. It consists of 17 convolutional layers and one fully connected layer, with the layers are stacked upon one another based on the concept of residual learning. Despite the introduction of shortcut connections in the network, there is no extra parameter nor computational complexity are. According to He et al. (2016), as the network depth increases, ResNet is capable of producing high accuracy and better results compared to previously proposed networks. A study by Rizvi et al. (2019) also evidently proves that ResNet18 outperforms the traditional classifier-based approach.

3 Methodology

Deep learning-based biometric identification has garnered significant attention due to its outstanding performance across various modalities. However, the accuracy of fingerprint identification can be affected by a range of factors, such as skin conditions, environmental aspects during acquisition, and variations among fingerprint sensors. This section describes the steps involved in the proposed performance analysis for two pretrained deep learning models, i.e., GoogLeNet and ResNet18. Figure 3 depicts the flow of the proposed performance analysis of the deep learning models on fingerprint identification.

Figure 3 Process flow of the proposed performance analysis



3.1 Fingerprint image databases

In this study, two fingerprint image databases are utilised, namely FingerDOS (Francis-Lothai and Bong, 2015) and FVC2002 DB1A (Maio et al., 2002). Both databases were acquired using optical sensors, and the specifications of the sensors are indicated in Table 2. FingerDOS comprises ten impressions per finger with minimal finger displacement on the sensor plate. For this study, only the index finger from right hand of 60 subjects are utilised from the database. Meanwhile, FVC2002 DB1A contains eight impressions per finger, some of which may have lower quality due to factors such as positioning of the finger and skin condition. This set of databases consists of a total of 800 fingerprint images from 100 fingers. Figure 4 depicts some samples of the fingerprint images from both databases.

Table 2 Sensor specifications

Database	*Sensor*	*Image size*	*Image resolution*
FingerDOS	SecuGen iD-USB SC	260 × 300	500 dpi
FVC2002 DB1A	Identix TouchView II	388 × 374	500 dpi

These two databases with different conditions are selected for the performance analysis so that a more comprehensive evaluation of the DCNNs model's identification ability can be performed. Figure 4(b) displays some samples of fingerprint images with rotational problems, incomplete images, and illumination differences from the FVC2002 DB1A database. In contrast, images from FingerDOS are more complete and have fewer issues regarding the quality or impressions, as shown in Figure 4(a). Since images from FVC2002 DB1A are more challenging compared to FingerDOS, a more rigorous comparison can be performed to evaluate the models' ability in handling bad fingerprint images. This will also allow for determining the limitations of the models and provide suggestions that may improve their performance.

Figure 4 Sample of fingerprint images taken from, (a) FingerDOS (b) FVC2002 DB1A

Note: Original images scaled down to 30% of its original size for display purposes.

3.2 Image preprocessing

A minimal image preprocessing technique is applied to both databases, which involve image registration using speeded up robust features (SURF) technique (Bay et al., 2008) and a cropping technique. In SURF technique, features from each image are extracted and used to calculate the transformation matrix that aligns the images.

3.2.1 Image registration

SURF technique is chosen because it is known for its robustness and speed for image alignment in various applications (Genc et al., 2020; Javed Mehedi Shamrat et al., 2022; Shahoud et al., 2022). The main parts of this technique are feature detection and description, feature matching, and transformation estimation. In the first part, interest points or keypoints are detected based on Hessian matrix approximation. Assume a point $X = (x, y)$ in an image I, the Hessian matrix $H(X, \sigma)$ in X at a scale σ is given by the following equation:

$$H(X,\sigma)=\begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \quad (1)$$

where $L_{xx}(X, \sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ for the image I at point X and likewise for $L_{xy}(X, \sigma)$ and $L_{yy}(X, \sigma)$.

After the keypoints are detected, feature descriptor for each keypoint is computed based on Haar wavelet responses in a region around the keypoint. The region is divided into smaller sub-regions and their Haar wavelet responses d_x, d_y are calculated. Each of the sub-region has a four-dimensional descriptor vector v depicted in the equation as follows:

$$v=\left(\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right) \quad (2)$$

The next step is to match the keypoints between the reference and target fingerprint images. The matching is based on comparing the feature descriptors using Euclidean distance. Keypoints with the closest descriptors are considered as matches. Figure 5 shows the matched SURF features in both images. Next, the matched keypoints are used to estimate the transformation between the two images. The target fingerprint image is warped to align with the reference fingerprint image. Figure 6 shows an example of a fingerprint reference image, target image, and registered image after applying SURF. As can be seen from Figure 6, the target image has been successfully aligned with the reference image. After the registration, both images, i.e., reference image and registered image, are in the same position and orientation.

Figure 5 Matched SURF features (see online version for colours)

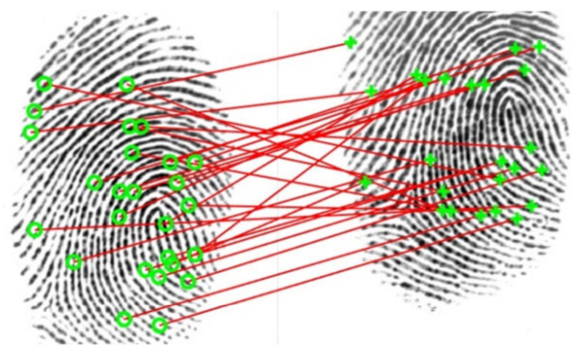


Figure 6 SURF-based image registration, (a) reference image (b) target image (c) registered image

(a) (b) (c)

3.2.2 Image cropping

The registered fingerprint image shown in Figure 6(c) includes area that is not relevant to the fingerprint. Therefore, image cropping is performed to extract a fixed-size region of 150 by 200 pixels. The aspect ratio of the region of interest (ROI) of the registered image is calculated by dividing the required ROI's width by its height. In this case, the aspect ratio is set as 150:200. If the selected ROI is greater than the aspect ratio, it means that the ROI is wider than desired, so the image is cropped horizontally. If the aspect ratio is smaller, it means the ROI is taller, therefore the image is cropped vertically to maintain the desired aspect ratio. Once the width and height of the ROI is adjusted, new coordinates (x, y) of the top-left corner of the adjusted ROI is calculated. The desired ROI is then cropped based on these coordinates with a fixed size of 150 by 200 pixels. The resulting cropped ROI contains only the meaningful fingerprint pattern. Figures 7(a) and 7(b) show the selected ROI and the cropped ROI, respectively.

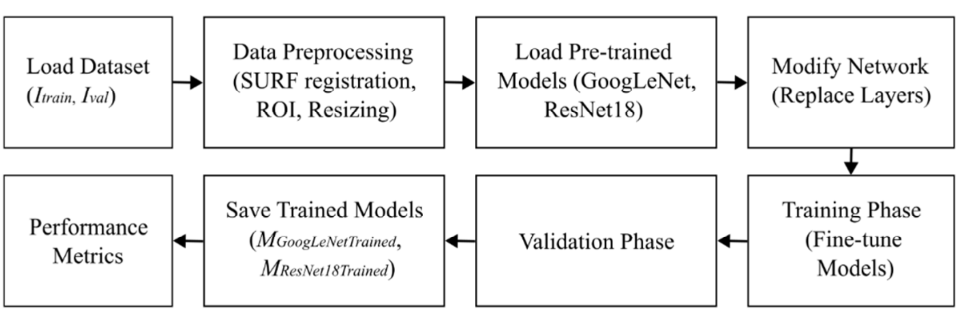
Figure 7 Image cropping, (a) ROI (b) cropped ROI

(a) (b)

3.3 *GoogLeNet and ResNet18 models training and validation*

A DCNN is a type of deep learning algorithm commonly used in image recognition and processing. It involves the use of convolutional layers that filter and process input data to extract meaningful features and patterns. In this study, two DCNNs are used, i.e., GoogLeNet and ResNet18, and transfer learning are applied to perform fingerprint identification. GoogLeNet has 22 layers and approximately 6.8 million parameters, which is significantly smaller than other DNNs of similar performance (Szegedy et al., 2015). ResNet18 is one of the smallest versions of ResNet. It consists of 18 layers, including 17 convolutional layers and one fully connected layer (He et al., 2016).

Figure 8 Training and validation phases



For each of the models, the training and validation phases are performed based on Algorithm 1. The block diagram representing the processes involved in the algorithm is shown in Figure 8. The fingerprint input images are first preprocessed, involving image registration and cropping. Then, the images are resized based on the model's parameter requirements. Since the pretrained models, GoogLeNet and ResNet18 require the image size to match their input size, the cropped images are resized to 224 × 224 before being fed into the training phase.

Algorithm 1 Models training and validation algorithms

Inputs: a set of training images, I_{train}, labels corresponding to training images, L_{train}, a set of validation images, I_{val}, labels corresponding to validation images, L_{val}, pre-trained models: GoogLeNet, $M_{GoogLeNet}$ and ResNet18, $M_{ResNet18}$

Outputs: trained models: $M_{GoogLeNet}$ and $M_{ResNet18}$, validation results: $R_{GoogLeNet}$ and $R_{ResNet18}$

1. Training phase:

For each I in I_{train}:

Detect keypoints and their descriptors in image I using the SURF algorithm.

Match these descriptors with those from a reference image I_{ref}.

Estimate the transformation matrix from the matched keypoints.

Apply the estimated transformation matrix to align I with I_{ref} (to find I_{reg}).

Define an ROI for cropping.

Crop I_{reg} to ROI, I_{crop}.

Resize I_{crop} to a fixed size of 224 × 224 pixels ($I_{resized}$).

Fine-tune GoogLeNet:

Replace the final classification layer in $M_{GoogLeNet}$ to match the number of classes in L_{train}.

Train $M_{GoogLeNet}$ using $I_{resized}$ and L_{train}.

Save the trained model as $M_{GoogLeNetTrained}$.

Fine-tune ResNet18:

Replace the final classification layer in $M_{ResNet18}$ to match the number of classes in L_{train}.

Train $M_{ResNet18}$ using $I_{resized}$ and L_{train}.

Save the trained model as $M_{ResNet18Trained}$.

2. Validation phase:

Validate GoogLeNet

Pass $I_{resized}$ through $M_{GoogLeNetTrained}$ to obtain predictions.

Compare these predictions with L_{val} using the performance metrics.

Record the performance metrics as $R_{GoogLeNet}$.

Validate ResNet18.

Pass $I_{resized}$ through $M_{ResNet18Trained}$ to obtain predictions.

Compare these predictions with L_{val} using the performance metrics.

Record the performance metrics as $R_{ResNet18}$.

The final classification layers of the pretrained models are first replaced with new layers to match the number of classes in the fingerprint dataset. Then, the modified networks are fine-tuned with the parameters: learning rate, α, 0.0003; momentum coefficient, γ, 0.9. The network weights are updated using the stochastic gradient descent with momentum (SGDM) rule:

$$\theta_{l+1} = \theta_l - \alpha \nabla E(\theta_l) + \gamma(\theta_l - \theta_{l-1}) \tag{3}$$

where θ_l represents the model parameters at the current iteration l, $\nabla E(\theta_l)$ is the gradient of the loss function E with respect to the model parameters at the current iteration l, and θ_{l-1} refers to the model parameters from the previous iteration $l - 1$. The training is performed with the following settings: GoogLeNet – mini-batch size: 8, max epochs: 8, ResNet18 – mini-batch size: 10, max epochs: 10. The trained models are then used in the validation phase for performance evaluation.

3.4 Performance analysis

In order to evaluate the effectiveness of each of the deep learning models, several tests are performed. The tests are based on the variation of the images and the number of images included in the training and validation phases. The variation of the images here refers to whether image preprocessing, i.e., image registration and cropping, is employed. It should be noted that the images from FingerDOS and FVC2002 DB1A databases may contain various noise, inconsistencies, and variations that could negatively impact the identification performance of the models. In the first test, the original fingerprint images from both databases without any preprocessing step involved are utilised. These images are only resized to match the input size of the models. The next test is based on preprocessed images. In the second test, the number of images involved in the training and validation varied. All tests are performed using MATLAB R2022b with a system configuration of 8 Gb RAM, i3 processors, and Windows 10 operating system.

3.4.1 The FAR, FRR and EER

Figure 9 shows the confusion matrix used to evaluate the performance of the deep learning models. The evaluation involves comparing the predicted data with the real data, or also known as the ground truth. Real data refers to the actual fingerprints belong to a subject and predicted data is referring to the output produced by the deep learning model used in the identification system. The predicted data consists of the matching or non-matching results between the input fingerprint and the available images in the datasets. The predicted matching includes both true positives (TP) and false positives (FP). TP occurs when the system correctly identifies a matching algorithm, while FP occurs when the system incorrectly identifies a non-matching fingerprint as a match. Meanwhile, for predicted non-matching, it consists of true negatives (TN) and false negatives (FN). TN happens when the system correctly rejects a non-matching fingerprint and FN happens when the system incorrectly rejects a matching fingerprint.

The confusion matrix helps evaluate the performance of each of the deep learning models in the fingerprint identification system based on its predictions and the actual ground truth. The effectiveness of the models is then measured using metrics such as false acceptance rate (FAR), false rejection rate (FRR) and equal error rate (EER). These metrics are calculated based on the equations shown in Table 3. A good biometric identification system is one that can produce low FAR, FRR and EER. A low FAR means the system is effective in differentiating between genuine users and impostors, while a low FRR indicates that the system is effective in correctly identifying genuine users. However, both FAR and FRR are inversely related, meaning when one decreases, the other tends to increase, and vice versa. Therefore, achieving a good balance between these two metrics is important to optimise the performance of the fingerprint identification. Thus, EER can be used to assess the overall performance of the system since it provides a balance between the two error rates. A lower EER indicates that the system has a better performance and higher accuracy.

Figure 9 Confusion matrix

		Real Data	
		True	False
Predicted Data	True	True Positive (TP)	False Positive (FP)
	False	False Negative (FN)	True Negative (TN)

Source: Choi et al. (2021)

Table 3 Performance metrics

Metric	*Equation*
FAR	$(FP) \div (FP + TN)$
FRR	$(FN) \div (TP + FN)$
EER	$(FAR + FRR) \div 2$, where $\lvert FAR - FRR \rvert$ is minimum

3.4.2 Other performance metrics

The accuracy and reliability of identifying individuals based on their fingerprint patterns depend heavily on the quality of the fingerprint images processed by the deep learning models. Therefore, the quality of the fingerprint images input into the deep learning models is evaluated using the following image quality metrics:

a Peak signal-to-noise ratio (PSNR)

The PSNR measures the quality of the registered fingerprint image compared to the reference image.

$$PSNR = 10 \cdot \log_{10}\left(\frac{Max^2}{MSE}\right) \tag{4}$$

where *Max* is the maximum possible pixel value of the image, and *MSE* is the mean square error (MSE) between the reference and registered images. Higher PSNR values indicate less distortion and better-quality images.

b MSE

This metric measures the average squared difference between the corresponding pixels of the reference and the registered image.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I(i, j) - K(i, j)\right)^2 \tag{5}$$

where M and N are the dimensions of the images, $I(i, j)$ and $K(i, j)$ are the pixel values of the reference and registered images, respectively. Lower MSE values indicate better performance.

c Structural similarity index (SSIM)

SSIM evaluates the perceptual similarity between the reference and registered images.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{6}$$

where μ_x and μ_y are the means of the reference and registered images, σ_x^2 and σ_y^2 are the variances, σ_{xy} is the covariance, C_1 and C_2 are the constants. A value closer to 1 indicates that the images are very similar to the original ones.

d Image quality index (IQI)

IQI provides an overall measure of image quality by considering structural distortions in the registered image relative to the reference image. IQI values close to 1 reflecting minimal degradation in image quality.

$$IQI = \frac{4\mu_x\mu_y\sigma_{xy}}{(\mu_x^2 + \mu_y^2)(\sigma_x^2 + \sigma_y^2)} \tag{7}$$

e Average difference (AD)

AD calculates the average absolute difference between pixel values of the reference and registered images. Lower values indicate better performance.

$$AD = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| I(i, j) - K(i, j) \right| \tag{8}$$

f Normalised cross-correlation (NK)

NK measures the similarity of fingerprint patterns between the reference and registered images by normalising their cross-correlation. A value of 1 indicates perfect positive correlation.

$$NK = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(I(i, j) - \bar{I} \right)\left(K(i, j) - \bar{K} \right)}{\sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(I(i, j) - \bar{I} \right)^2 \sum_{i=1}^{M} \sum_{j=1}^{N} \left(K(i, j) - \bar{K} \right)^2}} \tag{9}$$

where $\bar{I}$ and $\bar{K}$ are the mean pixel values in I and K, respectively.

g Structural content (SC)

SC compares the SC of the reference and registered fingerprint images by focusing on the sum of squared pixel values. The closer the SC value is to 1, the more structurally similar the two images are.

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I(i, j)^2}{\sum_{i=1}^{M}\sum_{j=1}^{N} K(i, j)^2} \tag{10}$$

h Maximum difference (MD)

This metric measures the maximum absolute difference between the pixel values of the reference and registered images. Lower MD values indicate that the processed image introduces minimal distortions.

$$MD = \max_{i,j} \left| I(i, j) - K(i, j) \right| \tag{11}$$

i Laplacian mean squared error (LMSE)

LMSE emphasises the edge preservation by applying Laplacian operator to the images. Lower LMSE values indicate that the model preserves the sharpness of fingerprint edges.

$$LMSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\nabla^2 I(i, j) - \nabla^2 K(i, j)\right]^2 \tag{12}$$

where ∇^2 is the Laplacian operator.

j Normalised absolute error (NAE)

This metric provides a normalised measure of the absolute error between the reference and registered fingerprint images. Lower NAE values indicate that the processed image closely resembles the original.

$$NAE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left| I(i, j) - K(i, j) \right|}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left| I(i, j) \right|}. \tag{13}$$

4 Results and discussion

The performance analysis of the deep learning models is divided into four parts, i.e., validation rates, identification rates, misidentification analysis and performance metrics. Firstly, the models' capability on unseen data is determined based on validation rates. Next, the identification rates are calculated to verify the models' ability to correctly identify fingerprint images. The comparison on the ability of the models to handle different fingerprint image variations is then described. Finally, the effectiveness and robustness of the models in handling different variations of fingerprint images are compared based on FAR, FRR and EER. The fingerprint images before and after registration are also evaluated based on ten performance metrics.

4.1 Validation rates

To evaluate the performance of GoogLeNet and ResNet18, three different settings are utilised to test images from FingerDOS and FVC2002 DB1A databases. These settings involved using 20%, 50%, and 70% of the images for training, while the remaining images were used for validation. The primary objective of these settings is to determine the identification performance that could be achieved as the size of the training set increased. The resulting validation rates for each setting of both databases are depicted in Table 4.

Table 4 Validation rates

Trained model	*Database*	*Images*	*Training datasets (%)*			*Average validation rates (%)*
			20	*50*	*70*	
GoogLeNet	FingerDOS	Original	90.00%	98.00%	100.00%	96.00
		Preprocessed	97.40%	100.00%	96.30%	*97.90*
	FVC2002 DB1A	Original	45.90%	48.39%	45.45%	46.58
		Preprocessed	76.27%	62.07%	77.78%	*72.04*
ResNet18	FingerDOS	Original	77.50%	100.00%	100.00%	92.50
		Preprocessed	94.81%	95.74%	96.30%	*95.62*
	FVC2002 DB1A	Original	36.07%	67.74%	63.64%	55.82
		Preprocessed	62.70%	55.17%	55.56%	*57.81*

GoogLeNet demonstrates consistently high validation rates across all scenarios. The model achieves an average validation rate of 96.00% when the FingerDOS database is used with original images. However, when preprocessed images are used, the average validation rate improves significantly to 97.90%. This suggests that preprocessing the images has a positive impact on the model's performance for this database. In contrast, the performance of GoogLeNet is dropped when it is validated using FVC2002 DB1A database. From Table 4, the average validation rate for the original images is 46.58%. The average validation rate improves with preprocessed images. It is evident that GoogLeNet performs better on the FingerDOS database than on the FVC2002 DB1A database.

ResNet18 also shows strong performance, particularly with the FingerDOS database. When using original images, the average validation rate is 92.50%, which further improves to 95.62% with preprocessed images. This indicates that preprocess the images improve the ability of ResNet18 in generalising to unseen data. However, its performance on the FVC2002 DB1A is lower than on the FingerDOS. The average validation rate with original images is 55.82%, which only slightly improves to 57.18% with preprocessed images. Although ResNet18 performs better than GoogLeNet on the FVC2002 DB1A, it is still not as effective as it is on FingerDOS.

In both models and databases, increasing the percentage of training datasets generally leads to improved validation rates. For example, with the FingerDOS database and preprocessed images, GoogLeNet achieves 97.40% validation rate with 20% training data, while it reaches 100.00% validation rate with 70% training data. This trend is consistent across most scenarios in Table 4. The results also show that the models achieved comparable validation rates when trained with only 20% of images from the databases. This suggests that the models are still effective even with a smaller training dataset. Both GoogLeNet and ResNet18 are capable models which perform better on FingerDOS with preprocessed images. This is predictable as the images on the FVC2002

DB1A databases are more challenging due to variations in image quality such as rotations, occlusion and illumination differences.

4.2 Identification rates

After training the models with preprocessed images, the identification rates are calculated to further evaluate their performance. During the testing phase, all available images are used, and a threshold value of 0.4 is set to determine a match. The resulting identification rates for both models and databases are presented in Table 5. The results indicate that the models performed differently between the two databases.

Table 5 Identification rates

Trained model	*Database*	*Training dataset (%)*		
		20	*50*	*70*
GoogleNet	FingerDOS	93.00%	*100.00%*	*99.00%*
	FVC2002 DB1A	88.75%	91.25%	98.75%
ResNet18	FingerDOS	*97.00%*	*100.00%*	*99.00%*
	FVC2002 DB1A	88.75%	86.25%	90.00%

With 20% training dataset, ResNet18 achieved a higher identification rate of 97.00% for FingerDOS, while GoogLeNet achieved a lower rate of 93.00%. However, for FVC2002 DB1A, both models achieved the same identification rate of 88.75%. As the training dataset is increased to 50% and 70%, there is an increase in the identification rates for both models. For FingerDOS, both models achieved the same identification rates of 100.00% and 99.00%. However, for FVC2002 DB1A, ResNet18 achieved slightly lower identification rates compared to GoogLeNet. This indicates that variations in the fingerprint images from this database affected the models' ability to accurately identify the fingerprint.

Based on the results, increasing the percentage of training datasets leads to improved identification rates. This is further supported by the performance of both models on the FingerDOS database, which contains a greater number of fingerprint impressions compared to FVC2002 DB1A. In particular, the FingerDOS database has ten impressions per finger, whereas the FVC2002 DB1A has eight impressions per finger. Having more training data benefits both GoogLeNet and ResNet18 in correctly identifying the fingerprints. With identification approaching 100% on the FingerDOS database, the identification capabilities of both models improve with larger datasets. Although the performance of the models slightly lower on the FVC2002 DB1A, both models still achieve promising identification rates even with smaller training datasets.

The results obtained from this study are then compared to existing methods, as shown in Table 6. The comparison is based on the results obtained during the testing phase of the models with 20% of the training dataset. On the FingerDOS database, ResNet18 and minutiae-based performed the best among other algorithms, with the highest identification rate of 97.00%. For the FVC2002 DB1A database, both GoogLeNet and ResNet18 achieved relatively higher identification rates compared to other algorithms. These findings demonstrate that the deep learning-based approaches in fingerprint identification are highly effective, even when trained with a relatively small percentage of the dataset.

Table 6 Identification rates comparison

Fingerprint identification algorithm	*Identification rates (%)*	
	FingerDOS	*FVC2002 DB1A*
GoogLeNet	93.00	*88.75*
ResNet18	*97.00*	*88.75*
FinSNet (Yoo et al., 2020)	96.00	83.75
Random forest-based (Saul et al., 2023)	94.00	85.00
CNN (Ghafoor et al., 2021)	88.00	66.25
Phase-only correlation-based (Francis-Lothai and Bong, 2017)	89.78	81.16
Minutiae-based (Krish et al., 2019)	*97.00*	87.50
Correlation-based (Sreeja, 2023)	36.00	32.50
Frequency domain (Khazaal and Mahdi, 2019)	79.00	52.50
Ridge-based (King et al., 2023)	39.00	35.00

However, the identification rates vary significantly between the two datasets, indicating the algorithms' varying effectiveness depending on the characteristics of the dataset. For instance, the RF-based method shows a moderate drop from 94.00% on FingerDOS to 85.00% on FVC2002 DB1A. CNN experiences a significant drop, from 88.00% on FingerDOS to 66.25% on FVC2002 DB1A. This implies that the method may not generalise well across different datasets. Other traditional methods, such as correlation-based and ridge-based approaches, perform poorly on both datasets, with identification rates significantly lower than others. The correlation-based method achieves just 36.00% on FingerDOS and 32.50% on FVC2002 DB1A, while the ridge-based method performs slightly better but remains low, at 39.00% and 35.00%, respectively.

Deep learning-based methods like ResNet18 and GoogLeNet perform better across both datasets compared to traditional methods like ridge-based or correlation-based approaches. The minutiae-based method also shows robust performance, indicating that traditional techniques that focus on fingerprint minutiae still hold significant relevance in the field. The phase-only correlation-based method is effective but not as competitive as deep learning-based approaches.

4.3 Misidentification analysis

The FVC2002 DB1A fingerprint database contains a variety of fingerprint images with different conditions, such as occlusion, rotations, and illumination differences. In comparison, the FingerDOS database contains higher quality images, yet there are instances where both GoogLeNet and ResNet18 incorrectly identify the fingerprints. In Figure 10, samples of fingerprint that are misidentified by GoogLeNet but correctly identified by ResNet18 are presented. Similarly, Figure 11 illustrates fingerprints that are incorrectly identified by ResNet18 but correctly identified by GoogLeNet. Meanwhile, in Figure 12, samples of fingerprint images misidentified by both models are presented. Each figure shows a sample from the FingerDOS and FVC2002 DB1A databases.

Figure 10 Fingerprint samples of misidentification by GoogleNet, (a) FingerDOS (b) FVC2002 DB1A

(a) (b)

Figure 11 Fingerprint samples of misidentification by ResNet18, (a) FingerDOS (b) FVC2002 DB1A

(a) (b)

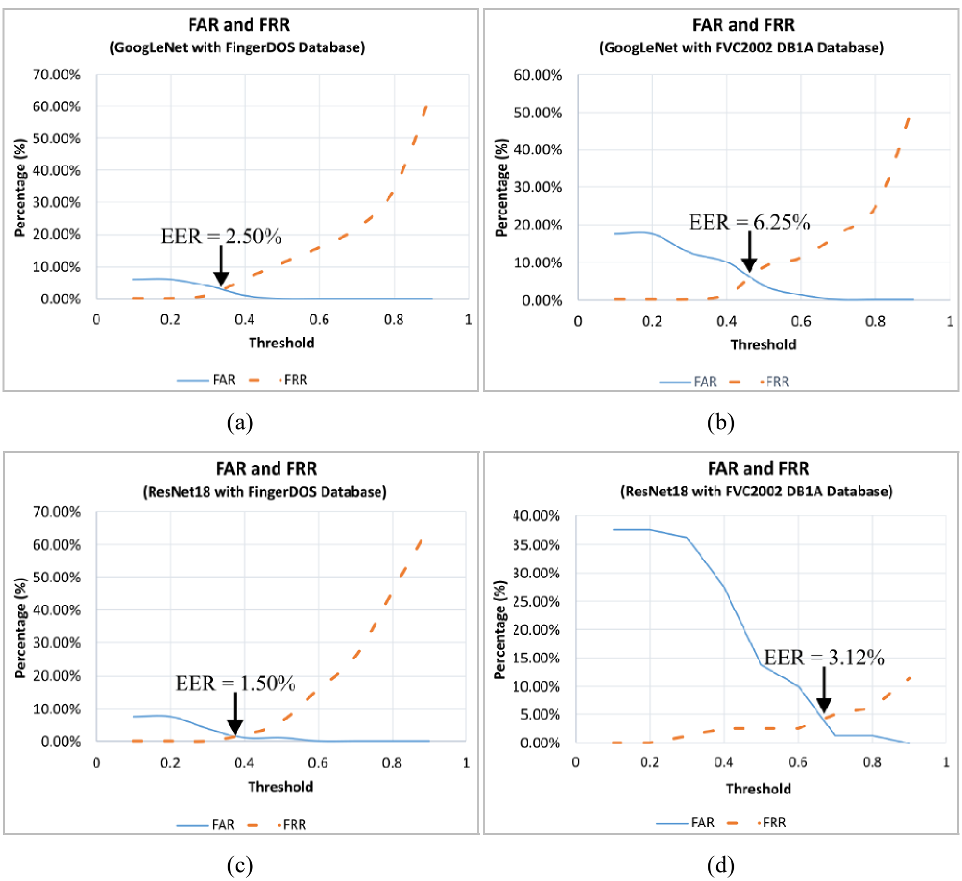
Figure 12 Fingerprint samples of misidentification by GoogleNet and ResNet18, (a) FingerDOS (b) FVC2002 DB1A

(a) (b)

Figure 10(b) and Figure 11(b) are both from the FVC2002 DB1A database. After registering and cropping the images, irrelevant background is still visible in the ROI. This is due to the way the fingerprint acquired, where the position and pressure of the finger on the fingerprint scanner is differ. The presence of this irrelevant background contributes to the misidentification by either GoogLeNet or ResNet18. Figure 11(a) and Figure 12(a) are from the same finger. However, due to lakes and spurs on the fingerprint ridge's structure shown in the latter figure, both models are unable to identify this fingerprint correctly. Additionally, Figure 11(b) and Figure 12(b) are impressions from another finger. The registration step manages to align the fingerprint, but due to the presence of irrelevant background as shown in Figure 11(b), it affects the models' ability to successfully identify the fingerprint.

Despite the preprocessing steps of image registration and cropping, the poor quality of these fingerprint images still poses challenges for the models, limiting their ability to correctly identify them. The ability of the models to handle these variations is affected by the variations and quality of the training data. Implementing image enhancement processes may further improve the quality of the fingerprint images and subsequently enhance the performance of the models.

Figure 13 FAR, FRR and EER, (a) GoogLeNet with FingerDOS (b) GoogLeNet with FVC2002 DB1A (c) ResNet18 with FingerDOS (d) ResNet18 with FVC2002 DB1A (see online version for colours)



4.4 FAR, FRR and EER

To further evaluate the performance of the models, the FAR, FRR, and EER values are calculated, and presented by the graphs shown in Figure 13. The EER, representing the intersection point of the FAR and FRR curves, is used to compare the performance of GoogLeNet and ResNet18. Based on the graphs, ResNet18 exhibited a lower EER values, i.e., 1.50% and 3.12% for FingerDOS and FVC2002 DB1A databases, respectively, when compared to GoogLeNet, with EER values of 2.50% and 6.25%. This evaluation demonstrates that ResNet18 outperformed GoogLeNet, despite having fewer layers. These results show that the number of layers in a DCNN is not the sole determinant of its performance.

Both models achieved a lower EER when evaluated with the FingerDOS database, while their EER is slightly higher for FVC2002 DB1A. As explained in Section 3.1, FVC2002 DB1A database contains more variation in images, making it more challenging compared to FingerDOS database. This variation in bad fingerprint images affects the performance of the models in identification, as reflected by the EER values obtained. In general, the low EER values suggest that the models are well-calibrated, with a good balance between FAR and FRR. These results indicate that the deep learning-based models are effective in minimising the number of false acceptances and rejections, resulting in high levels of accuracy in fingerprint identification.

4.5 Other performance metrics

Table 7 compares the image quality metrics for the two fingerprint databases, i.e., FingerDOS and FVC2002 DB1A, across ten image quality metrics, both with and without image registration. For the FingerDOS database, image registration generally improved the image quality, as indicated by a decrease in MSE from 11,951.34 to 11,227.77 and a corresponding increase in PSNR from 7.56 dB to 7.92 dB. These changes suggest that the images became closer to the original in terms of pixel-level similarity. Additionally, SSIM improved from 0.25 to 0.35, indicating enhanced structural similarity between images, while IQI increased from 0.38 to 0.43, reflecting better overall image quality. The NK also increased from 0.34 to 0.44, suggesting better alignment and similarity between images after registration. Despite these improvements, there is a slight increase in AD from 70.73 to 71.66, indicating a minor shift in average pixel intensity. The SC also increased from 1.02 to 1.22, indicating that the registered image has less SC than the reference image. The NAE increased from 0.41 to 0.66, suggesting a higher normalised error due to registration degradation.

In contrast, the FVC2002 DB1A database showed a different trend, where image registration generally led to a decrease in image quality. The MSE increased significantly, and the PSNR decreased from 10.53 dB to 8.96 dB, indicating a deterioration in pixel-level similarity. The SSIM also dropped from 0.34 to 0.28, showing reduced structural similarity after registration. Likewise, the IQI decreased from 0.39 to 0.33, indicating reduced alignment and similarity between images. SC also decreased from 0.99 to 0.79, suggesting a loss in SC post-registration. Despite these overall declines, decrement in the LMSE indicating improved preservation of high-frequency content, such as edges. However, the increment in NAE further suggesting that registration introduced misalignment or degradation.

Table 7 Performance analysis based on image quality metrics

Metrics	*FingerDOS*		*FVC2002 DB1A*	
	Without image registration	*With image registration*	*Without image registration*	*With image registration*
MSE	11,951.34	*11,227.77*	*5,936.34*	13,663.08
PSNR	7.56	*7.92*	*10.53*	8.96
SSIM	0.25	0.35	0.34	0.28
IQI	0.38	*0.43*	0.38	0.32
AD	*70.73*	71.66	0.39	0.33
NK	0.34	*0.44*	0.39	0.33
SC	*1.02*	1.22	0.99	0.79
MD	255.00	255.00	254.00	254.00
LMSE	38,112.03	*26,707.99*	20,946.24	*3,968.15*
NAE	*0.41*	0.66	*0.23*	0.51

These results indicate that while image registration improved quality metrics for the FingerDOS database, it negatively impacted the FVC2002 DB1A database. For the FingerDOS database, the improvement in image quality metrics after image registration contributed to the enhanced identification performance, as depicted in Table 6. This suggests the deep learning models could accurately classify the fingerprints. Meanwhile, the degradation in image quality for the FVC2002 DB1A indicates that the registration process may have introduced distortions or misalignments. As a result, the models may have difficulty to maintain high identification accuracy, as the loss of important image details prevents the models' ability to correctly identify fingerprints. This suggests that the effectiveness of image registration and the resulting image quality play an important role in the performance of fingerprint identification models.

5 Conclusions

This study demonstrates the effectiveness of two pretrained deep learning models, GoogLeNet and ResNet18, for fingerprint identification. Multiple tests have been conducted using two fingerprint databases, namely FingerDOS and FVC2002 DB1A. The results show that even with minimal image preprocessing, the deep learning models successfully identified fingerprints and achieved high identification rates compared to traditional method. The identification rates attained by both models varied across different percentages of training datasets, suggesting that it impacts the models' identification capabilities. However, the analysis of FAR, FRR, and EER metrics indicates that the models can perform well even with a reduced number of training datasets. This finding highlights the practical advantages of employing deep learning in identification systems with limited data availability. Moreover, the study revealed that the performance of the models slightly reduced when evaluated with lower quality fingerprint images, which are mostly sourced from the FVC2002 DB1A database. This observation suggests potential areas for improvement in future research. More advanced image preprocessing techniques that can enhance the quality of fingerprint images without introducing distortions could further boost identification accuracy. Furthermore, development of adaptive image registration methods for different fingerprint databases may solve the problems observed in this study. Finally, the study can also be expanded into other biometric modalities, such as face and palmprint recognition.

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