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Fingerprint Identification System based on VGG, CNN, and ResNet Techniques

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ABSTRACT

This study compares three different pre-trained deep learning models specifically designed for fingerprint identification. The first model uses Convolutional Neural Network (CNN), the second includes Residual Network (ResNet), and the third employs the Visual Geometry Group (VGG) approach. The subsequent comparative assessment reveals the CNN-based model's superior performance, with an impressive F1 score of 96.5%. In contrast, the ResNet and VGG models achieve F1 scores of 94.3% and 92.11%, respectively. These findings highlight the CNN model's ability to accurately identify fingerprints. Furthermore, a comparative analysis is performed between the obtained results and those reported in recent studies using the same dataset. This analysis evaluates the performance of the proposed models and compares them to previous research, increasing confidence in the results. In conclusion, this study shows that in terms of fingerprint identification, the CNN-based model performs better than the other models.

1. Introduction

Biometric identification systems stand out as the most adaptable and efficient means of verifying and authenticating individuals [1]. The overarching objective of biometrics is to reliably and robustly discern individuals based on their distinctive personal characteristics [2]. Human biometrics, characterized by standards for performance, acceptability, collectability, universality, uniqueness, permanence, and safety, plays a pivotal role in identity determination [3]. Notably, methods rooted in human biological traits are gaining prominence for their efficacy in establishing human identity, encompassing features such as facial identification, palm prints, iris patterns, retina scans, signatures, and fingerprints [4].

Fingerprints, intricate patterns formed by the incised skin at the tip of a human finger, possess inherent characteristics established before birth and enduring throughout an individual's maturation [5]. Despite their relatively small size, fingerprints encapsulate valuable information [6]. The extraction of features from fingerprints occurs at three levels individual points, ridge flow, and ridge direction capitalizing on the unique and stable ridge features that render fingerprint identification a vibrant area of research. Challenges, however, arise from factors such as moisture, dampness, dir

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and user behavior, contributing to the generation of low-quality fingerprint images necessitating noise reduction or compensation for adjacent areas [7] [8].While fingerprints are crucial for identifying individuals, it's important to recognize that some people may intentionally alter their fingerprints to avoid identification, especially in law enforcement contex
[9]. Despite this, fingerprints remain a cornerstone in biometrics due to their well-established uniqueness and persistence, finding applications in diverse fields including airport security, law enforcement, mobile access, and authentication [10]. The ubiquity of fingerprints in both civil and criminal applications underscores their wide-ranging utility for human verification and identification [11].This study employs three models for deep learning ResNet, VGG, and CNN to improve the accuracy of fingerprint identification. Each model, CNN, VGG, and ResNet, has distinct architectural characteristics that provide various advantages contributing to the optimization of fingerprint identification systems. The goal of using these models is to improve fingerprint identification's overall accuracy.The format of the paper is as follows: Important related efforts on fingerprint identification are included in Section 2. Section 3 lists the supplies and procedures in full. Section 4 discusses the fingerprint identification system. The results and discussion of the experiment are covered in Sections 5 and 6, respectively. Section 7 concludes with the conclusions.

2. Related works

In recent years, researchers have tried to use multiple methods in the field of deep learning to obtain high accuracy of fingerprint identification because of the importance it represents in verification and authentication processes. We will review some research papers that deliberately used the same Sokoto Coventry Fingerprint Dataset (SOCOFing) used in this work.

Jacob et al [12] proposed his method for using CNNs to study binary sex identification of African fingerprints. Four different models were compared: VGG-19, VGG-16, InceptionV3, and ResNet-50. The focus was on improving the performance of traditional deep models by addressing issues of limited available data. Data pre-processing techniques such as rotation, zoom, and reflection were also used to prepare the data. To expedite the training process and assess the models, transfer learning was employed to pre-train various models. Training loss criteria and accuracy were employed to assess the trained models. With a test accuracy of 71.9%, VGG-19 outperformed the others, followed by VGG-16 (72.3%), InceptionV3 (67.3%), and ResNet-50 (60.8%).

Spanier et al [13] proposed a method for improving gender identification using fingerprints by using data-driven artificial intelligence techniques. The approach involves adapting CNN architectures to meet specific requirements for image categorization. Common training techniques like data augmentation, normalization, and addressing class imbalance were employed. VGG was used for identification, and results were compared across four datasets. The accuracy reached 80% with the SOCOFing dataset, depending on fingerprint quality.

Al-Wajih et al. [14] utilized deep learning methods to classify fingerprint types. A meta-neural network was employed to analyze and predict fingerprint types. The NIST and SOCOFing datasets were used for training and evaluation. The model achieved high verification accuracy, approximately 94%, for fingerprint types. The importance of shape-based fingerprint recognition was emphasized for enhancing the precision and effectiveness of fingerprint identification systems.

Chhablani et al. [15] proposed the use of deep neural networks to improve the performance of computer vision models by learning about interactions between superpixels. They developed a hybrid model that combines a Graph Neural Network (GNN) to manage the relative information of the image's superpixels and a CNN to handle spatial information. The model's performance was extensively tested on seven different image identification datasets. The results show that incorporating superpixel relative information processed by GNN can enhance the performance of a standard CNN-based vision system, achieving an accuracy of 93.58%.

Jeong et al [16] suggested the advancement of fingerprint identification system. The market for smart door locks that incorporate extra technologies like Bluetooth connectivity and fingerprint identification is growing. To extract features and determine if fingerprints match, the CNN model structure is employed. This study proposes a new door lock design that minimizes the user's fingerprint and enhances the appearance of the current door lock that is visible to the public. The accuracy percentage of the results was a remarkable 95.93%.

Yilmaz et al [17] proposed an innovative method for improving thumbprint identification in criminal investigations. The fingerprint enhancement layer and the fingerprint identification layer comprise the two sections of the technique. In the first step, low-quality fingerprint photos were converted into higher-quality images. Additionally, a second proposed model based on Gabor filters is being created to monitor the accuracy of fingerprint device recognition. The discriminator and generator CNN-based neural network models are used to automatically learn the translation function. the suggested Pix2Pix model performs better at fingerprint detection than the baseline model. There was 96.8% accuracy in the outcomes.

Giudice et al [9] concentrated on locating modified fingerprints, identifying the types of modifications used, and identifying the gender, hand, and fingers. A deep neural network technique based on the Inception-v3 architecture is used in the research. Activation maps, which indicate which areas of the neural network to concentrate on in order to locate the alterations, are also included in the study. Accuracy of up to 92.52% for gender identification and 92.18% for finger identification on the SOCOFing dataset.

Oladele et al. [18] proposed a deep learning approach to classifying gender from fingerprints for each of the five types of fingers, and the results were compared and evaluated using the trained model's results, which were based on a CNN structure. The trained model was tested with fingerprint sample images from 20 people representing the five finger types, and an overall accuracy of 72% was obtained.

3. Material and Methods

This paper employs three prevalent models widely utilized in the domain of deep learning and fingerprint identification. The selected models for this study encompass VGG, CNN, and ResNet.

3.1 VGG-16 Model

In order to win the ILSVR (Imagenet) competition in 2014, the convolution neural net (CNN) architecture VGG16 was used. VGG16 consists of three completely linked layers, five max-pooling

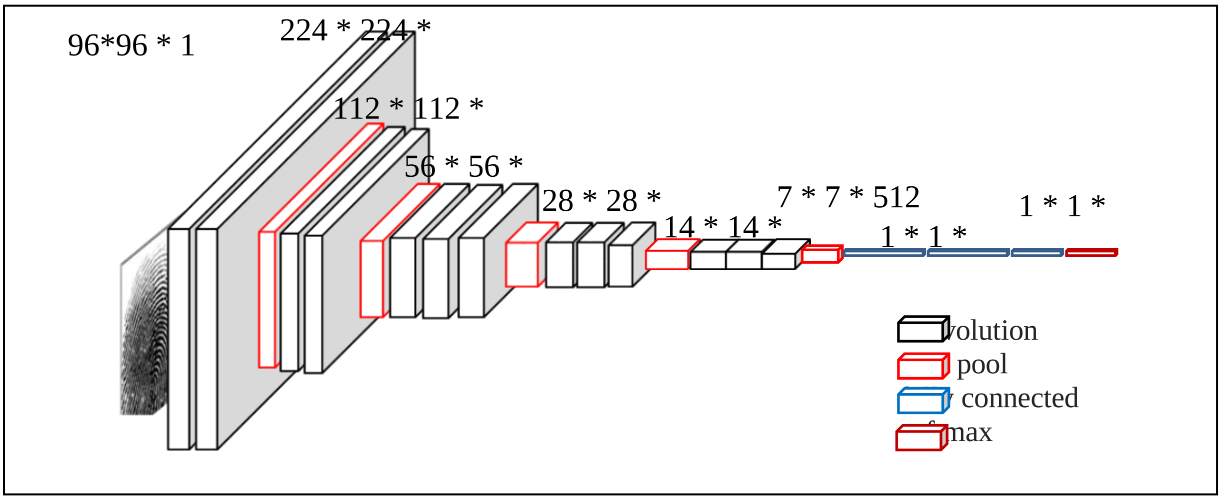

Fig.1. VGG-16 architecture

layers, and thirteen convolutional layers, as shown in Figure 1. That is the meaning behind the model name VGG16. There are 64 filters in the first block; this is doubled to 512 in the next blocks. This model is completed with two fully connected hidden layers and one output layer. The 4096 neuron counts in the two completely connected layers are the identical. The number of categories in the SOCOFig dataset is represented by the 600 neurons that make up the output layer [19], [20], [21].

3.2 ResNet-50 Model

Another groundbreaking architecture in the domain of deep learning is ResNet, introduced in 2015. Figure 2 depicts the ResNet architecture. Comprising two convolutional layers and a non-parameterized shortcut connection, ResNet introduced a novel approach by transmitting the output of the preceding block unaltered to the subsequent block as in Equation 1 [22].

$$y = f(x) + x \qquad (1)$$

where y: represents the ultimate output of the network for the current block. x is a representation of the current block's input signal. The function f(x) represents the output of the convolutional layers in the current block.

The subsequent modification of the residual block, implemented in ResNet-v2 in 2016, omitted the ReLU activation on the shortcut connection, further improving performance [23].

The Max Pooling Layer makes use of a 3x3 pooling window, while the Convolutional Layer, the initial layer, has 64 channels and a 7x7 filter. Similarly, a 1x1 filter, 64 channels, and a 3x3 filter make up the third and fourth layers. 3x3 and 256 channels, in that order. The filter size stays the same and the number of channels doubles in the following two layers. This pattern persists until the Average Pooling Layer, which employs the Average Pooling window, and the 600 nodes in the Fully Connected Layer, the final classification layer, which is determined by the categories of the data set.

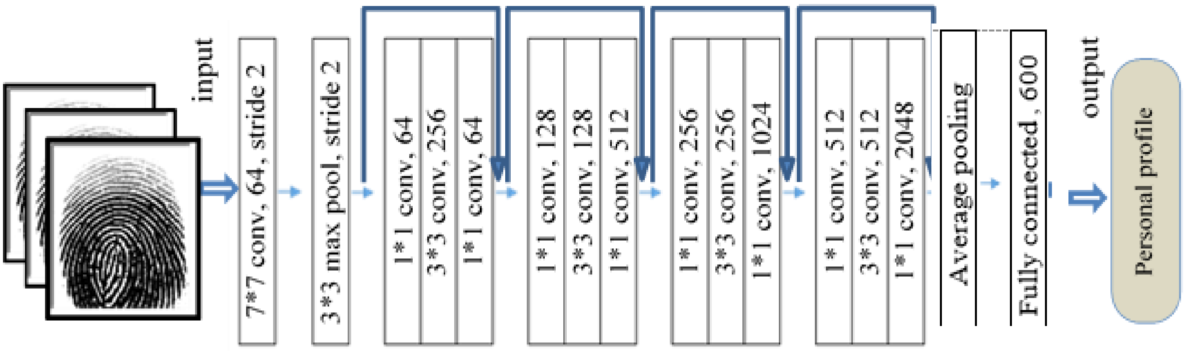

Fig. 2. ResNet architecture

3.3 CNN Model

Using a CNN for object detection was the initial method of object and person recognition. However, a significant amount of training data and a long training period are typically required for the basic use of a CNN [24]. Prioritizing the recognition of basic patterns like lines and curves above more intricate patterns like faces and objects is how CNN layers work. Therefore, it is conceivable to say that employing a CNN might grant computers eyesight [25]. The input, hidden, and output layers make up the CNN. The picture pixel matrix serves as CNN's input, while the image feature that results from the convolution computation serves as its output [26].

The input data is subjected to convolutional operations by the convolutional layer using filters. A matrix can be used to represent a filter. The filter slides horizontally with a specific step size during the convolutional process, as shown in Figure 3, and then moves vertically with a new step size for the subsequent horizontal slide, and so on, until the entire image has been scanned. The feature map is a new matrix created by the collection of filter outputs. The stride's breadth and height are the measurements of the horizontal and vertical steps. The matching CNN's architecture specifies the precise amount of feature maps to be employed [27].

The structure can be described by saying that 64 channels are present in a 1*1 filter that makes up the first layer. It increases to 224*224*64, while the next layer, Convolutional Layer, consists of filters of size 4*4 and contains 512 channels, and increases to 28*28*512, and the contrast continues until the last layer, which includes a filter of size 1*1 and contains 600 channels, based on the number of categories in the dataset.

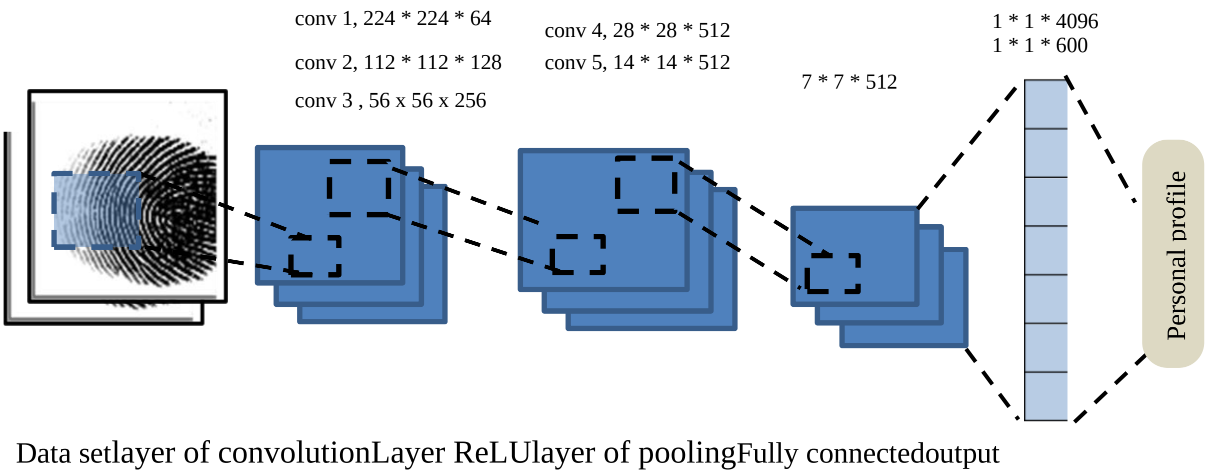

Fig.3. Basic CNN operations

4. Fingerprint Identification System

Fingerprint identification systems serve the principal objective of authenticating individuals by leveraging the unique and distinct patterns inherent in their fingerprints. Comprising four key stages as Figure 4, the initial phase involves the acquisition of fingerprint images, commonly referred to as the dataset stage. Subsequently, the acquired fingerprint data is subjected to preprocessing through advanced image processing techniques, aimed at enhancing the overall image quality. Following this enhancement, minutiae points, ridge patterns, and other distinctive features are extracted utilizing specific techniques. During the authentication or identification stage, a comparison is executed based

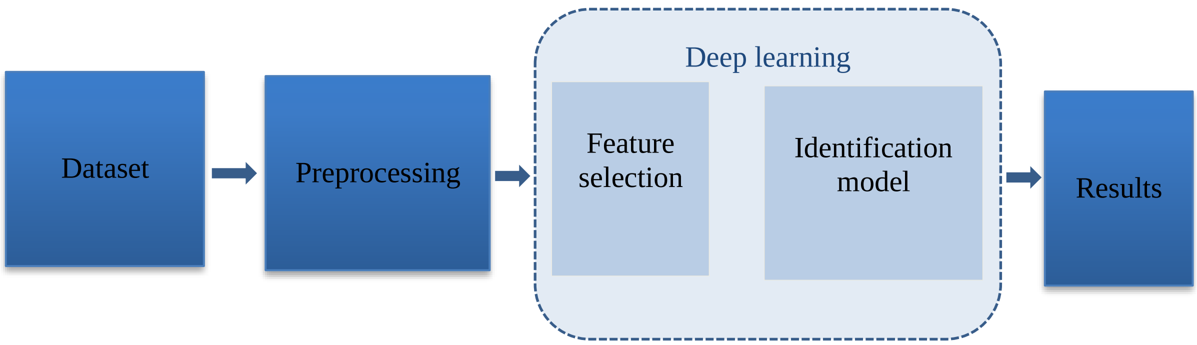

Fig.4. Phases of fingerprint identification systems

on evaluation metrics to ensure the accurate verification of individual identity. These stages will be discussed below in more detail:

4.1 Dataset Stage

In this study, the SOCOFing dataset is utilized, encompassing 6,000 fingerprints from a cohort of 600 African subjects, with each subject contributing 10 fingerprints Image. The image size in the data set is 1 x 96 x 103. All individuals in the dataset are aged 18 years or older. The dataset is noteworthy for its unique features, which include labels for 600 categories of gender, hand, and finger names. In addition, the collection provides artificially modified fingerprints with three different degrees of modification: obliteration, central rotation, and z-cut. The STRANGE toolkit, a ground-breaking framework created for the realistic synthesis of mutations in fingerprint photos, was used to create these changes [28].

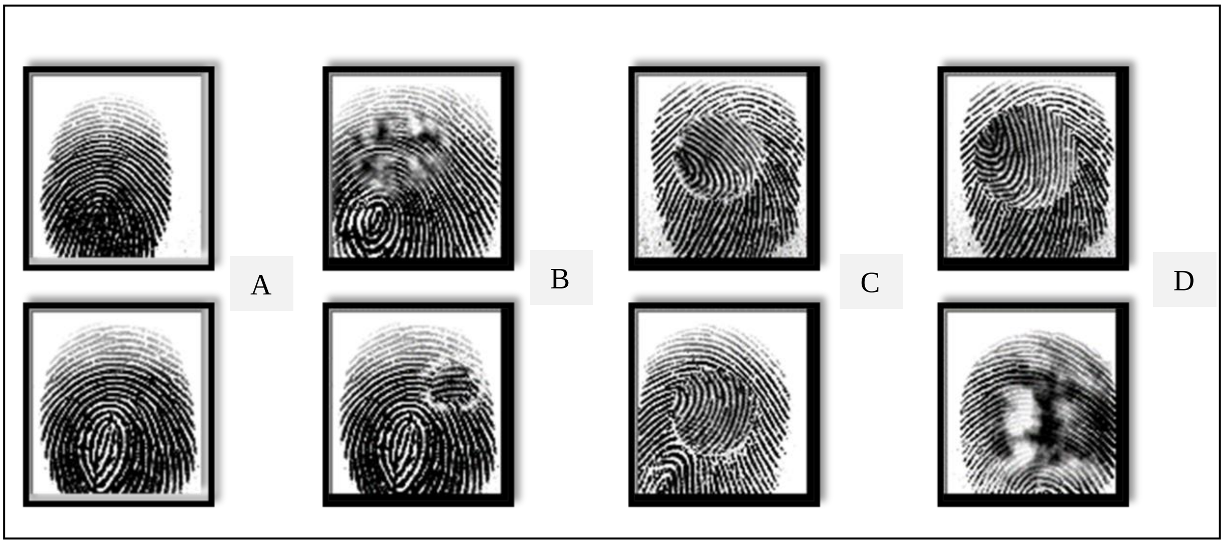

Fig. 5. A: Real, B: Altered-Easy, C: Altered-Medium, D: Altered-Hard, the components of the data set

4.2 Preprocessing Stage

The preprocess image function converted the image to grayscalethis is to preserve structural information and reduce data complexity, resized it to a training size (96 x 96), normalized the pixel values, and resampled the matrix for model input. These steps ensure that the image is properly formatted for future Deep learning tasks.Processing methods for images such as enhancement of quality, enhancement of contrast, and noise reduction are used to improve the quality of images and are thus considered important parameters for improving the precision of this work. In order to increase the precision and effectiveness of the identification process, we also separated the data set into 80% training and 20% testing.

4.3 Feature selection and definition stage

This study uses three distinct deep learning models CNN, VGG, and ResNet for feature extraction and identification. These models systematically filter out and prioritize relevant features during training, which enhances efficiency and reduces computational complexity by excluding irrelevant features. The extracted features are crucial for identifying data during testing, showcasing the essential role of these models in improving the identification process. It was found that the parameters affecting the training process of the three models were equally effective: The batch size was 32, its error rate had been 0.0001, and there were 30 epochs. These conditions generalized to all the models trained in this work.

4.4 Evaluation stage

Table 1 shows how the parameters such as Precision, Recall, F1 Score, and Accuracy were employed in the evaluation to assess the models' performance. Precision measures the accuracy with which positive results are recognized (Equation 2), whereas recall evaluates the ability to accurately recall positive results (Equation 3). F1 Score is also a balanced determine that combines precision and recall to provide an estimate of the whole performance (Equation 4). Accuracy assesses the overall accuracy of a model or test (Equation 5). It is necessary for fingerprint recognition. The parameters are determined mathematically using the next equations [29], [30], [31].

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$\text{F1 score} = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{4}$$

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FN} + \mathrm{FP}} * 100 \tag{5}$$

5. Experiment results

A Windows 10 machine with an Intel(R) CoreTM i5-3317U processor, 6GB of RAM, and an Intel(R) HD Graphics 4000 GPU was used to train the models. Tensorflow version 2.4 and Keras API version 2.4 were used to build the models in Python. The system was tested and trained on approximately 57,273 images. Figure 6 displays the training and validation accuracy of the three models. It also displays the training and validation loss of the model. It is noticeable that these values vary according to the architecture followed. It is worth noting that the models were trained under the same conditions of estimating the parameters and distributing the data between the training, testing and validation set.

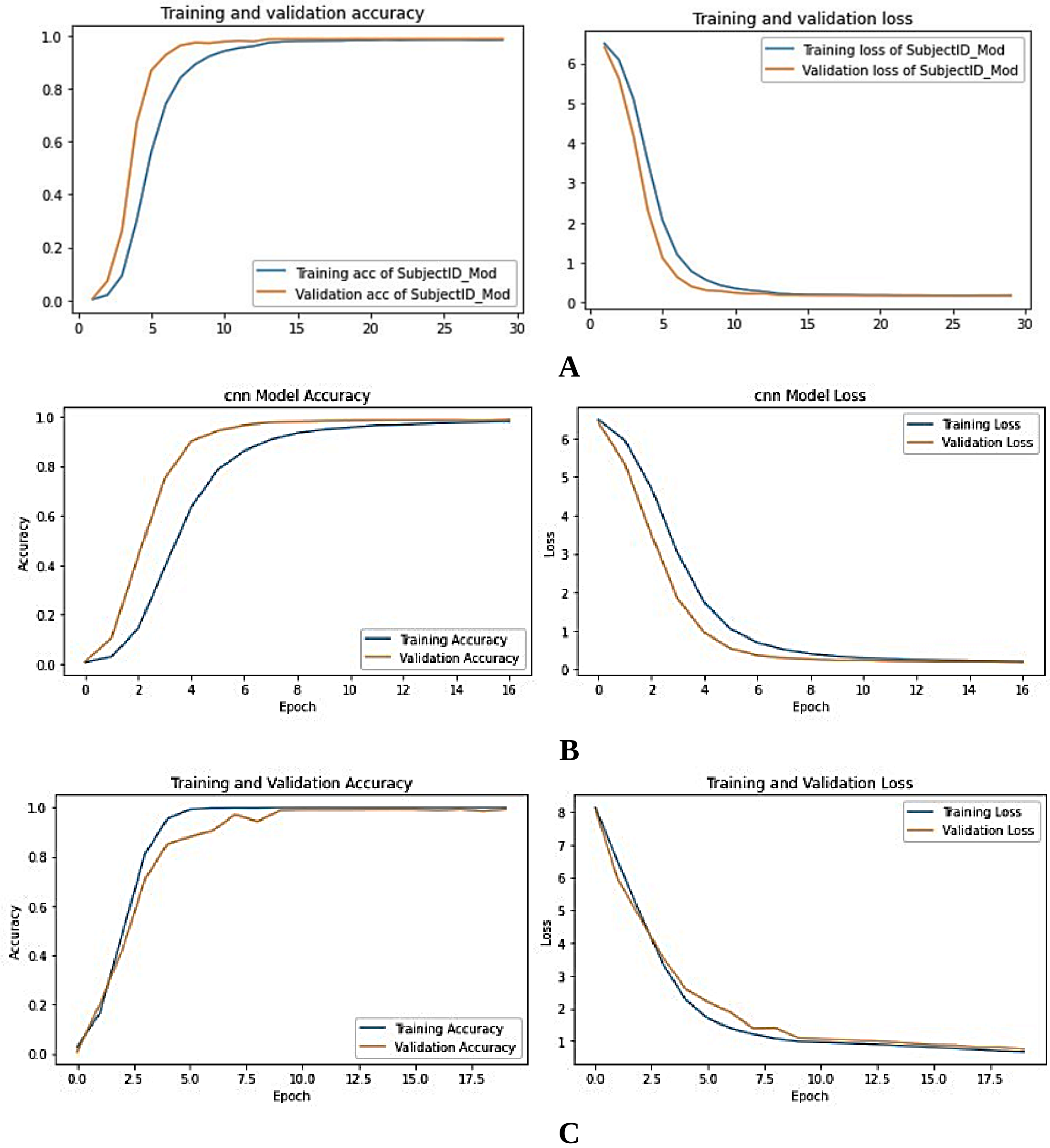

Fig. 6. A. VGG model, B. CNN model, C. ResNet model

The system's performance was evaluated using a test set of 5,000 images, including 3,000 observed images from the model and trained from the training data, and 2,000 unseen images from the model, where the test fingerprints are passed to the system to identify them and identify appropriate individuals. The three models' findings are displayed in Table 1.

Table 1. F1 score and accuracy value for the models used.

Met. / Alg.	F1 Score	Accuracy	Precision	Recall
VGG	92.11%	92.74%	91.74%	92.74%
ResNet	94.30%	94.49%	94.18%	94.49%
CNN	96.50%	96.79%	96.30%	96.79%

6. Discussion

Table 2 shows that this work produced higher accuracy results than previous studies. In this work, CNN was used to achieve a precision of 94% [14] and 96.5%, demonstrating its clear superiority in increasing image identification accuracy.Figure 7 representing the Confusion matrix supports the power of the model in correctly identifying images. This demonstrates that CNN is a strong and efficient algorithm for increasing image recognition accuracy.

On the contrary hand, we found that VGG accomplished 80% accuracy within previous research [13], but 92.11% precision in this work. Although VGG produced good results, it was less effective at enhancing fingerprint identification accuracy than CNN. ResNet had previously achieved 60.8% accuracy [12], but it now achieves 94.3% accuracy. This indicates which the avatar used in this study made a significant contribution to increasing image identification accuracy.

It is important to point out that these contrasts are based on the same data as in this and previous studies. As a result, these contrasts can be thought of as more reliable and valid. Other factors that influence accuracy include data size and distribution, as well as processing methods. Based on the findings of this study, we can conclude that CNN and enhanced algorithms such as ResNet helped to improve image identification accuracy.

Table 2: Comparison of this work with the latest previous work that uses the same dataset

Ref.	Size	Algorithm	Accuracy
[12]	6,000	ResNet	60.8%
[13]	6,000	VGG-16	80%
[9]	55,273	CNN	92.18%
[15]	6,000	CNN,GNN	93.58%
[14]	6,000	CNN	94%
	57,273	VGG-16	92.11%
Proposed work	57,273	ResNet	94.3%
	57,273	CNN	96.5%

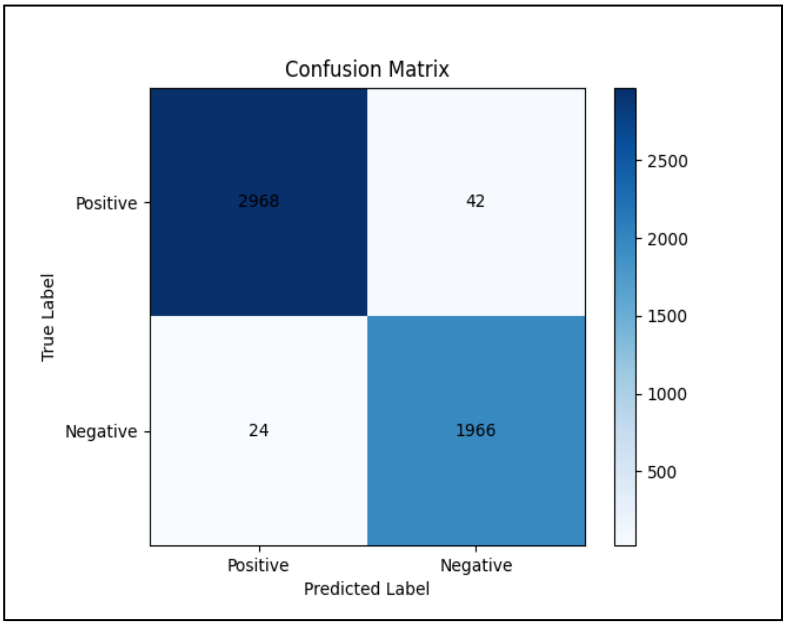

Fig.7. Confusion matrix for CNN model

7. Conclusion

The study emphasizes the critical importance of utilizing available data and comparing results to previous research in order to advance scientific knowledge in this field. One of the study's limitations is the fact that the deep models used are complex and require a lot of computational resources and time to train and evaluate. However, certain recent developments can be identified that may guide future efforts in this field, such as the development of developed deep learning models, dealing with environmental challenges, and using bigger and more varied data to achieve more efficient systems. It is recommended that more research and development be done to achieve practical applications based on accurate and reliable fingerprint identification. These future works help to develop advanced fingerprint identification systems, improve their performance, and increase the overall efficiency of fingerprint identification.

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نظام التعرف على البصمات بأستخدام تقنيات VGG , CNN و ResNet

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معلومات البحث

الاستلام	16 اذار 2024
القبول	3 حزيران 2024
النشر	30 حزيران 2024

الكلمات المفتاحية

التعرف على البصمات، التعلم العميق، VGG، CNN، القياسات الحيوية، Socofing.

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الملخص

تقارن هذه الدراسة بين ثلاثة نماذج مختلفة للتعلم العميق تم تدريبها مسبقًا ومصممة خصيصًا للتعرف على بصمات الأصابع. يستخدم النموذج الأول الشبكة العصبية التلافيفية (CNN)، ويتضمن النموذج الثاني الشبكة المتبقية (ResNet)، ويستخدم النموذج الثالث نهج المجموعة الهندسية المرئية (VGG). ويكشف التقييم المقارن اللاحق عن الأداء المتفوق للنموذج المعتمد على شبكة CNN، حيث حصل على F1 score مرضية تبلغ 96.5%. في المقابل، حقق نموذجا ResNet و VGG F1 score بنسبة 94.3% و92.11% على التوالي. تسلط هذه النتائج الضوء على قدرة نموذج CNN على تحديد بصمات الأصابع بدقة. علاوة على ذلك، يتم إجراء تحليل مقارن بين النتائج التي تم الحصول عليها وتلك الواردة في الدراسات االسابقة باستخدام نفس مجموعة البيانات. يقوم هذا التحليل بتقييم أداء النماذج المقترحة ومقارنتها بالأبحاث السابقة، مما يزيد الثقة في النتائج. في الختام، توضح هذه الدراسة أنه فيما يتعلق بتحديد بصمات الأصابع، فإن النموذج المعتمد على CNN يعمل بشكل أفضل من النماذج الأخرى.

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