Integration of EfficientNetB0 and Machine Learning for Fingerprint Classification

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A fingerprint is a common form of biometric technology used in human identification. The classification of fingerprints is crucial in identification systems because it significantly reduces the time required to identify a person and allows for the possibility of using fingerprints to distinguish between genders and identify individuals. Fingerprints are the most reliable identifiers because they are unique and impossible to fake. As a method of personal identification, fingerprints remain the best and most trustworthy. Fingerprint classification is crucial in a wide variety of settings, such as airports, banks, and emergencies involving explosives and natural disasters. This study proposes a deep learning strategy for determining whether a fingerprint belongs to a male or female person. With the help of pre-trained convolutional neural networks (CNN) in computer vision and an extremely powerful tool that has achieved significant success in image classification and pattern recognition. This work includes the use of the SOCOFing fingerprint dataset for training and employing a state-of-the-art model for feature extraction called EfficientNetB0, which was trained on the ImageNet dataset. Then feeding the extracted features into a principal component analysis (PCA) to decrease the dimension of these features and random forest RF classifier for fingerprint classification. Lastly, the tests showed that the proposed strategy outperformed the previous categorization methods in terms of accuracy (99.91%), speed for execution time, and efficiency.

Povzetek: V članku je opisana metoda globokega učenja za ugotavljanje, ki skoraj 100% ugotovi, ali prstni odtis pripada moškemu ali ženski.

1 Introduction

Fingerprint identification is more reliable and efficient than ever before. The features of fingerprint, such as the ridge period, ridge ending, ridge flow, and delta or core points are all used by automatic fingerprint identification systems (AFIS) in the enrollment and verification processes. Several factors affect matching performance, including the user's age, race, gender, scars, finger pressure on the acquisition sensor, and the quality of the fingerprint scanner device[1]. Moreover, the pictures' or fingerprint alignment data's resolution should be adequate to accommodate augmentation operations like translation, rotation, or skin distortion. The ability to extract fine details may also be influenced by background noise and image rotation[2].

The level of accuracy and reliability of automated fingerprint identification systems (AFIS) is capable of reaching very high standards. However, when poor-quality, altered, or only partially complete fingerprint photos are used, AFIS's performance significantly degrades. Due to the intentional or accidental destruction of the dermatoglyphic crests seen on fingers, the AFIS system's error rate significantly increases when using a very large database of fingerprints during the identification process. The most significant benefit of CNN-based classifiers is feature extraction and classification can be performed automatically without the need for human intervention[3]. Deep learning alleviates this burden by drastically decreasing the computational cost of searching for a fingerprint image in large datasets. Expert pattern recognition is one reason why deep neural networks have attracted so much attention from researchers. The purpose of this research is to apply deep learning, transfer learning, and other machine learning techniques to the problem of fingerprint image gender-type classifying[4].

The following are some of the main contributions to this work: a) Extracting features and classifying fingerprint images using a pre-trained convolutional neural network (CNN) model (EfficientNetB0) and transfer learning technique to classify a fingerprint's gender as male or female[5]. b) The proposed model uses EfficientNetB0 for feature extraction, principal component analysis (PCA) for feature reduction, and random forest (RF) for fingerprint classification[6].
c) Evaluating the proposed method's precision in comparison to other contemporary approaches. The paper is set up as follows: in Section 2, which provides a review of comparable works from prior studies for researchers. The research methodology is presented in

Section 3 including the dataset description together with the pertinent theoretical and experimental information. Section 4 presents the results findings and analysis of the fingerprint gender classification. In Section 5 we discussed the compare results of our work with those from previous studies. Finally, the conclusions and future works are described in Section 6.

2 Related works

Over the years, many scholars have examined fingerprint classification, employing a wide range of methods and aiming to accomplish various categorization goals.

Deep learning, which was developed out of research into neural networks, paves the way for modern machine learning[7]. One of its main aims is to develop a neural network that can analyze and interpret information in much the same way that a human brain does. Recognition and classification performances of existing algorithms have been surpassed in some deep learning application scenarios where certain conditions are met. Numerous previous studies have tackled the fingerprint classification problem from a variety of angles, each with its own unique set of methodologies. In this section, we will focus on those points. Previous studies are summarized in Table 1 below.

In 2018 Shehu et al.[8]refined a complex CNN and developed a transfer learning solution using the CNN while training on the SOCOFing dataset. The accuracy of gender, hand, and finger classifications are tested; these are 75.2%, 93.5%, and 76.72%, respectively.

In 2018 Shehu et al[13].Convolutional Neural Networks (CNNs) were used to sort legitimate fingerprints from fakes in the SOCOFing dataset and, if the latter were found, to categorize the type of alteration into one of three categories: obliteration, central rotation, and Z-cut. An accuracy of 98.55% percent was achieved using their method.

A technique was developed by Giudice and colleagues in 2020, which utilizes a deep neural network trained with the Inception-v3 architecture, to recognize gender, hand, and fingers. Additionally, this method can detect changes made to fingerprints and determine the specific type of alteration. The method was tested on the SOCOFING dataset and demonstrated an accuracy rate of 98.21%, 98.46%, 92.52%, 97.53%, and 92.18% for identifying fakes, alterations, gender, hand, and fingers, respectively. In 2020 Fattahi et al.[14] have been centered on the use of Convolutional Long Short-Term Memory networks (LSTMs) to recognize damaged fingerprints with an accuracy of greater than 95%.

In 2021 Moga et al.[15] offers a solution to the issue at hand by employing a Siamese network comprised of two VGG-16 neural networks in fingerprint recognition authentication systems, achieving an average accuracy rate of 87% on test data.

In 2022 Ibitayo et al.[10] designed a method for identifying a person's gender based on their fingerprints, with an accuracy of 96% using CNN and 94% using SVM (for gender classification). In 2022 Al-Wajih et al.[11] using the SOCOFing dataset, the proposed CNN model achieved an accuracy of 89% when classifying fingerprint classes (index, middle, ring, and little fingers). In 2022 Sravanthi et al.[12] fingerprint verification using a Support Vector Machine was shown to be effective, and the results were compared to those obtained using a novel Nave Bayes classifier with accuracy: 87.28% for Naive Bayes, and 83.01% for SVM. In 2022 Ganesh et al.[16] they improved fingerprint recognition accuracy to 97.83% by recommending a deep Convolutional Neural Network (CNN) for fingerprint image identification for crime detection.

As was previously mentioned, several researchers have been putting forth effort into fingerprint classification, and they are anticipating positive outcomes from their datasets. They use a wide variety of image preprocessors for noise reduction by using filters or techniques to enhance the quality of the images. In conclusion, state-of-the-art models, some of which have been pre-trained on a massive dataset, are used in most deep learning classification methods. Due to its intricate design, training requires a significant investment of both time and resources. Modest datasets, a simpler architecture, and less computational time are required to improve the accuracy of model performance.

Table 1: A summary of the literature on fingerprint classification techniques.

2018	Shehu et al. [8]	CNN	75.2
2020	Giudice et al. [9]	Inception-v3	92.52
2022	Ibitayo et al. [10]	CNN	96
		SVM	94
2022	Al-Wajih et al. [11]	CNN	89
2022	Sravanthi et al. [12]	Naïve Bayes	87.28
		SVM	83.01

3 Research methodology

3.1 Sokoto coventry fingerprint (SOCOFing) dataset

We used the academic research biometric fingerprint database SOCOFing for our study; which was obtained from the Kaggle website. The dataset contains 6,000 fingerprint scans from 600 unique individuals, with 10 fingerprints per person, making up for the real and fake fingerprint portions of the dataset. And also three variants of these fingerprints, each with 17934, 17067, and 14272 labeled images, easy, medium, or hard, respectively, Figure 1 shows the distribution of the variants. All images are grayscale and have a resolution of 1×96× 103 pixels (color x width x height) with BMP extension[17] The pictures have metadata, that includes the person's identifier, the hand of the finger is on, the name of the finger itself, the finger's gender, and alternation type. The modified fingerprints are constructed from the original fingerprints that have been obliterated, centrally rotated, and z-cut to produce new shapes as shown in Figure 2[18].

Data preprocessing is essential before feeding the information into the model. The efficiency of the model's learning is enhanced if the data and images are of higher quality. The researchers in this study used several data preparation strategies to ensure the highest quality of results. At first, every picture in both collections was converted to image size (224 widths and 224 heights). After that, shuffled all the data to avoid overfitting. And augmentation images by using (featurewise center, and vertical-flip). At last, the full Real dataset (6000 samples) was divided into 80% (4799 samples) for training,20% (1201 samples) for validation, and the samples for testing data.

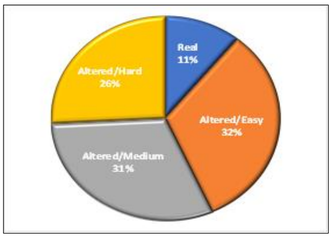

Figure 1: SOCOFing dataset classes.

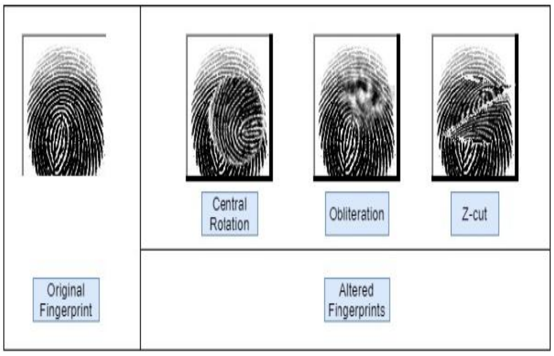

Figure 2: Types of Fingerprint in SOCOFing.

3.2 Transfer learning and EfficientNetB0

A significant quantity of data and computing power is needed for the deep neural network, it could take several hours, days, or even weeks to train a deep network, which is a major issue to solve. As a general description of A convolutional neural network (CNN) architecture, convolutional layer aggregation that executes feature extraction, pooling layer, and fully connected layers are effective for identifying.

Fortunately, there are numerous pre-trained deep neural networks CNN available, including GoogleNet, Inception, Alexnet, VGG19, ResNet, MobileNet, and many others. These pre-trained neural networks are trained using very large datasets of up to one million training photos on the ImageNet dataset[19]. Therefore, rather than creating a deep neural network from scratch, the pre-trained network can be used after certain modifications. This technique of altering a pre-trained network is known as "transfer learning," and it can categorize photos into 1,000 object categories. By freezing or unfreezing layers, transfer learning can also be utilized to fine-tune hyperparameters. Either through introducing a custom classifier and training an architecture with random initial weights using a fresh dataset or by retraining the architecture's weights while freezing the weights of particular layers alone[20].

In 2019, Google Brain proposed EfficientNet, which has excellent feature extraction capabilities.
It has fewer parameters and more accuracy than other traditional convolutional neural networks, and it uses the fewest FLOPS (the number of floating point operations that can be executed by a computing entity in one second) to make inferences[21]. The image at the network input has a size of (224, 224) pixels. A multi-objective neural architecture search is used to construct the EfficientNet baseline network, which is subsequently scaled in terms of depth, width, and resolution to strike a balance between them. Central to the network is a portable inverted bottleneck convolutional module (MBConv). The following is a definition of the compound scaling method:

$$\text{depth: } d = \alpha^{\phi} \tag{1}$$
$$\text{width: } w = \beta^{\phi} \tag{2}$$
$$\text{resolution: } r = \gamma^{\phi} \tag{3}$$
$$\alpha \,.\, \beta^2 .\, \gamma^2 \approx 2 \tag{4}$$
$$\alpha \geq 1 \,,\, \beta \geq 1 \,,\, \gamma \geq 1 \tag{5}$$

where α, β, and $\boldsymbol{\gamma}$ can be determined using a small grid search. The feature extraction for a fingerprint gender classification is obtained by using the state-of-the-art for EfficientNetB0, the architecture shown in Figure 3[22].

3.3 Principal component analysis(PCA)

Feature reduction involves mapping the feature vector from a higher to a lower dimension. Numerous technologies can be employed, including genetic algorithms, ICA, PCA, and linear discriminant

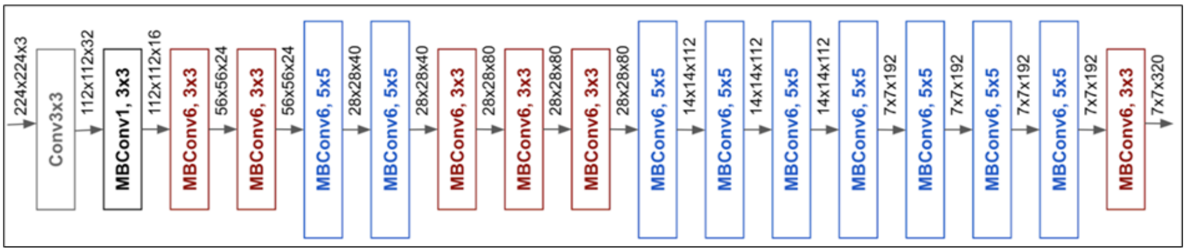

Figure 3: Architecture of baseline EfficientNet-B0.

Analysis (LDA)[23]. Where PCA, is a dimension reduction and data analysis technique. To retain as many of the original data features as possible, PCA linearly projects high-dimensional data samples into low-dimensional space. [24].

After CNN's pre-trained feature extraction model extracts features, the features may contain greater dimensions that need more computation and redundant information.Therefore, before classifying fingerprints, we use a principal component analysis(PCA) to reduce the noise and the feature dimension before fingerprint classification [25]. PCA is a statistical method for discovering correlations between features and shrinking the dimensionality of the data. Memory and processing can be greatly decreased by the reduced dimensionality before the classification, we used a dimensionality reduction technique on the combined feature maps. The fingerprint image falls into the same category but may vary depending on noise levels, illumination, etc, there may be certain similar patterns known as primary components. The image's primary features must be preserved and the original features must be replaced with a linear combination[26]. The performance of the classifier algorithms can be enhanced by reducing the number of components in principal component analysis (PCA), which can also significantly reduce memory and computation requirements[27].

3.4 Random forest (RF) classifier

Decision trees (DTs) are built using ensemble methods, and the classifier used in this study is a Random Forest (RF). A random forest is a collection of decision trees that are drawn at random from the input feature set. It takes input data, trains several models, collects each model's prediction, and then uses a voting mechanism to determine which solution is best[28]. In this study, fingerprints are identified using decision trees and random forests, and the fingerprints category (labels) are used as the new input figures for training a binary classifier using the supervised approach of the RF algorithm, following feature reduction using the unsupervised learning PCA algorithm [29].

3.5 EfficientNetB0 optimization

Since the EfficientNetB0 model had already been trained on the 1,000-category ImageNet dataset, we were able to tailor it to our task, reducing the number of trainable parameters while increasing accuracy.
We used two ways to improve the standard structure of the EfficientNetB0 model and get to the best model for research on fingerprint classification. The proposed work in its two forms can be summed up as follows, as shown in Figure 4.

3.5.1 First strategy

We trained the models on Kaggle's cloud environment on the Google Cloud Platform. The models were configured in a Python 3.7.12 environment (Jupyter Notebook) using the Keras API 2.6.0 with Tensorflow 2.6.4 and CUDA/CuDNN dependencies for GPU100 acceleration (1 Nvidia Telsa P100 GPU, 2 CPU cores, and 13 Gigabytes of RAM). After loading our dataset SOCOFing with preprocessing and augmentation, we split the dataset. The settings of the parameters and hyperparameters selected for the EfficientNetB0 model are presented in Table 2. Firstly, we loaded the pre-trained model EfficientNetB0 and performed a convolution with an input image size 224x224, freezing the ImageNet weights for transfer learning and feature extraction. Then we fine-tuned the unfrozen layers at the top of the model using the Globalaveragepooling(GAP) layer, flatten layer, and 2 fully connected (Dense) layers with 512 parameters. We used an output layer with a sigmoid activation function for binary fingerprint gender classification. To avoid overfitting, we added a Dropout layer and batch normalization layer for speeding up the training.

Table 2: EfficientNetB0 hyparameters and tuning.

Hyperparameters	Setting
Input Size	224 x 224
batch size	32, 10
seed	42
optimizer	Adam
learning_rate	1e-3
epochs	200
loss function	binary- cross entropy
EarlyStopping	50 patience for 'min' Val-loss and 'max' Val-accuracy not improving
Total params	4,975,780
Trainable params	2,273,585
Non-trainable params	2,702,195

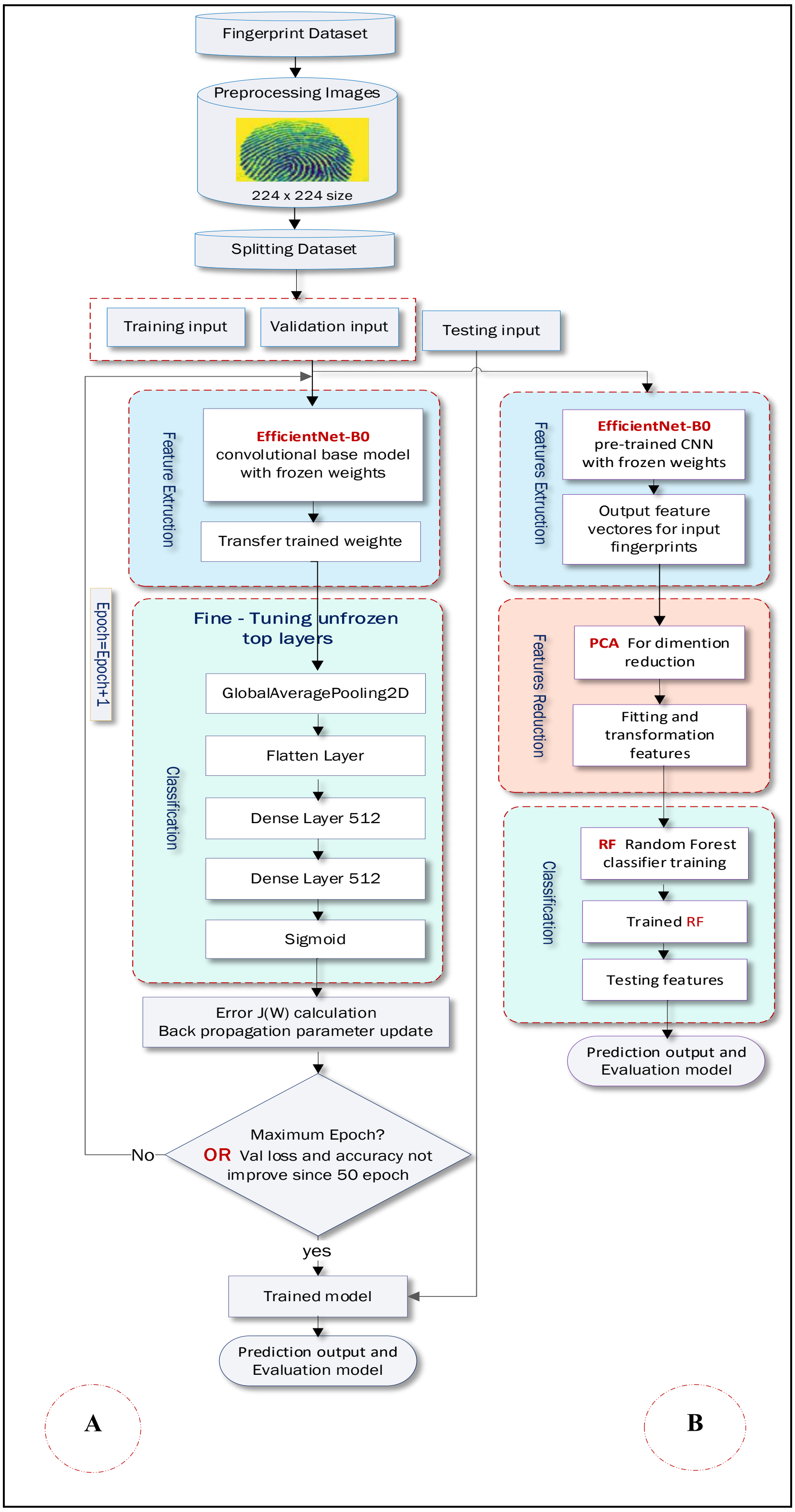

Figure 4: An illustration of proposed strategy in two approaches ;
A: EfficientNetB0 model B: EfficientNetB0-PCA-RF

3.5.2 Second strategy

Based on the features extracted by transfer learning, we used the deep learning pre-trained model EfficientNetB0 with (freezing weights). Then machine learning algorithms PCA with RF for dimensionality reduction of feature space and classification respectively for gender fingerprint classification. The parameters setting for PCA to reduce features extracted by EfficientNetB0 and for RF for binary class(1/Male and 0/Female) are explained in Table 3.

Table 3: PCA and RF parameters setting.

Techniques	Parameters	Value
PCA	n-PCA-components	600
RF	n-estimators	50
	max_depth	32
	random state	42

4 Results

The model's performance is assessed by evaluating how well it performs during both the training and testing phases. Each training period involves training the model using the training dataset, followed by the evaluation of the validation dataset. The evaluations of the algorithm's performance take into account samples from the test set that have never been used previously.

In light of this, it can be assumed that the model will generalize well if it is successful in predicting.

Figure 5 below illustrates the geometry of the binary confusion matrix for the proposed method. Accuracy, recall, precision, and F-score are also used to evaluate the approach. The performance measures, which are generated from the confusion matrix are displayed in Eqs. (7-10) comprised of four values: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (NN) (FN). In the formulas, TP represents a prediction that the positive class will be positive, TN represents a forecast that the negative class will be negative, FP represents a prognosis that the negative class will be positive, and FN represents a forecast that the positive class will be negative[30].

$$\text{Accuracy} = (TP+TN)/(TP+FP+FN+TN) \quad (7)$$

$$\text{Precision} = TP/(TP+FP) \quad (8)$$

$$\text{Recall} = TP/(TP+FN) \quad (9)$$

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \quad (10)$$

5 Discussion

Our work in this paper is based on using the SOCOFing datasets for human gender fingerprint classification purposes. To improve deep learning classification performance, PCA is used for dimensionality reduction of the extracted image features.

Comparing the suggested model to a typical EfficientNetB0 implementation, the new model had greater accuracy and required less training time. The accuracy of the proposed EfficientNetB0-PCA-RF was 99.91 percent, while that of the standard EfficientNet-B0 network was only 82.76 percent. And in comparison to previously published research using different techniques [8], [9], [10], [11], [12] summarized in Table 1. In [8], [11] the structure was built for CNN from scratch, and [10] used CNN and SVM, whereas [12] used CNN and Naïve Bayes for various fingerprint classifications. Figure 6 shows the comparison of the accuracy of our proposed methods with the previous studies. Additionally, the proposed model outperformed other state-of-the-art models such as Inception-v3 used in [9]. By using feature extraction and reduction techniques, we were able to speed up the classification process and improve its accuracy, which allowed us to use fewer resources without sacrificing precision.

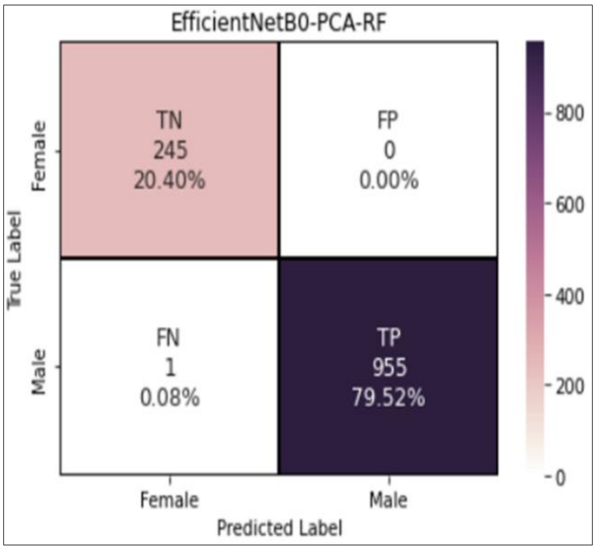

Figure 5: Confusion matrix for second strategy.

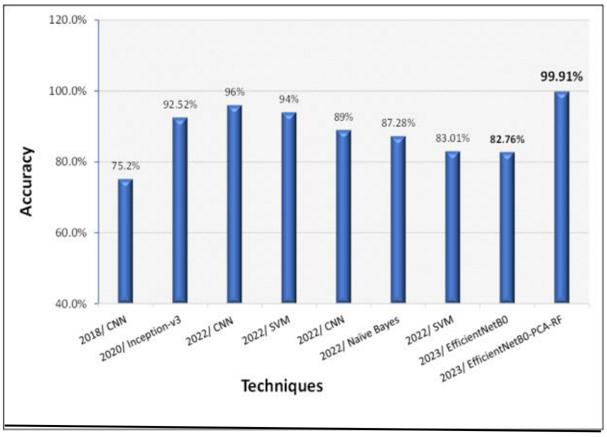

Figure 6: The comparison of the accuracy score of proposed methods with the previous studies

6 Conclusion

In this study, we show that the proposed method for fingerprint classification works well according to the results. The first method, by using a pre-trained model, EfficientNetB0 to extract features and the classification of fingerprint gender. In the second method, after features were extracted with EfficientNetB0, then PCA was used to reduce features dimensionality, and RF was used to solve the fingerprint binary classification problem.

The second proposed method outperformed the first in speed and accuracy when it came to feature extraction and fingerprint gender categorization on the SOCOFing dataset, despite using fewer trainable parameters. The evaluation results showed that the first method had a validation accuracy of 82.76%, an 80.19 % precision rate, an 87.32% percent recall rate, an F1-score of 83.60%, and an execution time (0:11:45.619517). The second method had a 99.91% accuracy rate, a 99.89% precision rate, a 100.0% percent recall rat, an F1-score of 99.94%, and an execution time (0:00:06.781987).

In future research, The goal is to use additional optimization methods on a wide variety of pre-trained CNNs by comparing the performance of identification and classification systems using deep learning-based CNNs with different biometrical datasets, optimizing the network structure to increase the learning speed for fast identification, and enhancing the performance of images with noise.

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