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Performance comparison of four pre-trained deep learning models for fingerprint-based gender classification

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Abstract

Fingerprints Recognition System is known to be the best tool for verification, and identification because it adopts the use of human biological traits that are unique and permanent throughout one's lifetime. It is widely used in surveillance, forensic investigation, border control access and criminal investigation. This paper aims to develop a model that is capable of classifying an individual's gender from fingerprint images using four pre-trained Convolutional Neural Networks architectures. The goal is to evaluate their performances, comparing their results, and also comparing their results with other state-of-the-art models using the Sokoto Coventry Fingerprint (SOCOFing) dataset. To achieve our aim, an experimental approach was adopted where features were extracted, and different pre-processing techniques such as cropping, resizing, and rotation were done; the dataset was balanced with down sample technique. The dataset was split into a ratio of 80:10:10 for the training, validation, and testing set respectively. That implies that for 1,000 males, we randomly split to 800 for training, 100 for validation, and 100 for testing. The same was repeated for females. So, a total of 1,600 data was used for training, 200 for validation, and 200 for testing. We employed four deep learning transfer models, which are ResNet50, DenseNet121, EfficientNet-B0, and VGG19. EfficientNet-B0 emerges as the best model, obtaining the best results across all metrics with 74.69% accuracy and 82.79% Area Under Curve (AUC), closely followed by ResNet50. The consistent balance between sensitivity and specificity across all models indicates robust learning without gender bias, while the strong AUC scores confirm meaningful classification capability.

Keywords: Fingerprints; Images; Gender; Deep Learning Model; Pre-trained Architecture

1. Introduction

Biometrics is an essential area of human traits that is uniquely identifiable [1]. It is used to analyse the biological information of an individual person on the basis of behavioural and physiological features [2]. These attributes are advantageous in so many forms, such as unpredictable, non-transferable, and a high level of security against fraudulent acts and unauthorised access. Various biometric techniques have been used over decades for identification and verification purposes; these include capturing of photos, thumb printing of fingers, and the like [3].

The high level of insecurity in terms of data, information, and access to unauthorised areas has drawn massive attention to the field of biometrics, with an increased use of biometrics technologies [4]. Nowadays, there are several technologies used for identification and verification. These include fingerprint, signature, speech, handwriting, gait, body shape, ears, face, iris, palm, DNA, token, and password [5].

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Among these biometric technologies, the fingerprint recognition system is prominent, and has distinctive features that are fundamentally used in numerous applications such as personal authentication, criminal identification, verification, and border control access [6] [7].

Fingerprints have been widely adopted because of their uniqueness and acceptability [8]. The structural pattern of fingerprints, such as ridges, minutiae points, and ridge thickness, can be used to differentiate between two fingerprints and find out their resemblance [9]. It is a pattern of ridges and valleys, where the ridges are dark lines, and the valleys are white areas between the ridges [10] [11].

Human beings have several soft biometric traits known as demographic features, such as gender, age, ethnicity, that make recognition and identification easier for individuals [12]. Gender determination or classification can be used to classify unknown individuals or victims as either a male or a female for easier identification [12] by extracting related characteristics from fingerprints [13] [14]. Determination of gender from a fingerprint is a bit difficult compared to face or voice [15] [16].

Most of these studies adopted the use of Discrete Wavelet Transformation (DWT), Local Binary pattern, Dominant Un-Decimated Wavelet Coefficient [17] as a Machine Learning Algorithms for classification and determination. Few studies adopted the efficient performance of Deep Learning Algorithms, such as Convolutional Neural Networks, and related Pre-Trained Algorithms.

Deep Convolutional Neural Network is known for its best classification accuracy, due to its computational capability to tackle complex challenges of image classification [18]. This research work leverages Deep Learning techniques and uses four pre-trained Convolutional Neural Network architectures, such as ResNet50, DenseNet121, EfficientNet-B0, and VGG19, to classify the gender of an individual using the SOCOFing dataset. The performance of each of them will be compared, and evaluation would also be compared with the state – of- art model.

2. Literature

Fingerprint structural patterns, such as ridge density and ridge characteristics, have long been used as an indicator to determine the gender of people [19]. Globally, fingerprints are generally classified into three types: whorl, loop, and arch, as shown in Figure 1.

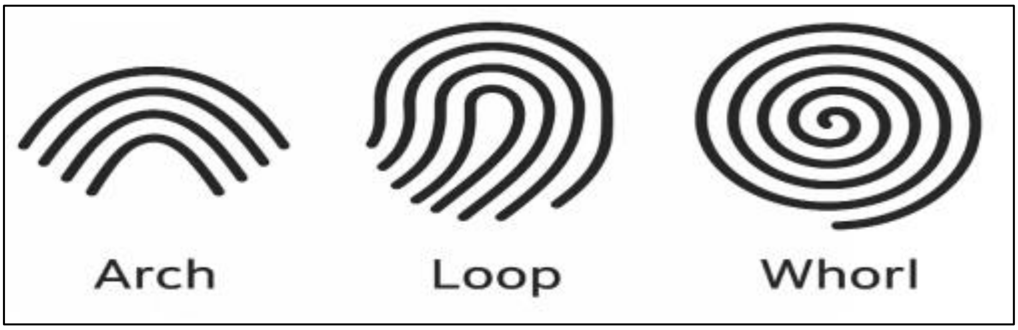

Figure 1 Types of Fingerprint Patterns

The whorl pattern consists of plain whorl and accidental whorl, the loop pattern is divided into right loop or left loop, and the arch pattern is subdivided into plain arch and tented arcs [20] [21].

The significant application of image classification in computer vision and related fields is as a result of the large amounts of data with complex operations that can be performed by deep learning [22]. Among the various categories of Deep Neural Network is Convolutional Neural Network (CNN) [23], recognising for its speedy processing power [24], ability to extract intricate attribute and patterns from raw data [25], and accurately used in object detection and prediction.

Over the years, various researches have been carried out in the area of gender classification through fingerprint analysis using different computational and machine learning techniques.

Similarly, [26] developed a fingerprint-based gender classification model using Discrete Wavelet Transformation (DWT) and K- nearest Neighbour (KNN) classifier with the approach that employed Frequency Domain to extract energy based features from fingerprints images. The images were decomposed into different coefficients used to train the KNN classifier and Euclidean Distance to determine whether a fingerprint belonged to a male or female. However, they recommended the combination of spatial and frequency domain features which are machine learning algorithms.

The study by [27] on Fingerprint Classification using Support Vector Machine, focused on models that classify fingerprint images into arches, loops, whorls using Support Vector Machine (SVM) classifiers with FVC2000 and FVC2002 public datasets. The model achieved 92.5% accuracy. However, the model focuses on fingerprint pattern classification rather than gender classification that can help to narrow down the search for a criminal or victim.

Another study by [28] on a fingerprint-based automatic Human Gender identification model, presented a model that automatically determined gender from fingerprints to enhance biometric systems. The study utilised Contrast Adaptive Histogram Equalization (CLAHE) as a pre-processing technique, and feature extraction through Discrete Wavelet Transformation (DWT). The Feed Forward Backpropagation Neural Network was used for classification, and the model achieved 96.6% accuracy. However, the study did not leverage the power of deep learning for accurate classification.

In a related study, [29] proposed a gender classification method from fingerprints using Local Texture Analysis (LTA) and Local Binary pattern (LBP) techniques with the aim at creating a robust model rather than traditional ridge-count approaches. The pre-processing stages include cropping, greyscale conversion, binarisation with textual feature extraction using LBP and Rotation Invariant Uniform LBP to form the local textual descriptors. The model achieved high experimental results of 95.88%, and the study demonstrated that texture-based LBP features are better for gender determination under varying illumination. However, it was recommended that integrating texture and frequency- based methods will yield better precision.

A deep learning approach for automatic gender determination from fingerprints was introduced by [30]. They presented a model that is capable of learning complex fingerprint patterns directly from the images with a novel hybrid approach that combined the Convolutional Neural Network (CNNs) and Long Short-Term Memory (LSTM) Network, enhanced with Dynamic Horizontal Voting Ensemble (DHVE) techniques that selected the best models during training. Using Histogram Equalisation and Bilateral Filtering for pre-processing and enhancement of contrast. Their hybrid model achieved 99% accuracy on the local dataset and 98% on the SOCOFing public dataset and outperformed ResNet-34, VGG-19, and EfficientNet –B3. However, they recommended incorporating fingerprint quality indices to further enhance biometric identity systems.

Similarly, [6] conducted a research on Gender Classifications from Fingerprint-Images using Deep Learning Approach, the study discovered how deep learning models can be used to predict gender without manual pre-processing. Convolutional Neural Network architectures such as VGG19, ResNet-50, and EfficientNet-B3 were used. The network was trained using Adam optimiser and dropout regularisation. The model's best accuracy was 97.89% with EfficientNet-B3 on the training set.

This study [10] explored the potential of Convolutional Neural Network (CNN) for gender classification from the fingerprints to extract important features from the fingerprints. The study utilised a three-layer Convolutional Neural Network (CNN); the experimental findings achieved 99% accuracy classification, confirming that fingerprints contain adequate and distinctive features that can predict a person's gender efficiently.

In a related study of Fingerprint recognition based on collected images using Deep Learning Technology by [31], an effective matching model for fingerprint verification systems was suggested, acknowledging that images produced from scanning devices may differ slightly across captures. The study utilised a Deep Convolutional Neural Network (CNN) of fifteen layers that operated in two stages. The first stage involved image capturing, augmentation, and pre-processing, and the second stage is based on feature extraction and image matching. The experimental findings suggested that Deep CNN techniques have highly promising and better accuracy with 100% on both the training and validation datasets.

Finally, [24] investigated a study on Gender classification from fingerprints using a hybrid CNN_SVM. The study aimed to improve gender determination and prediction performance on both the deep learning advanced feature extraction of Convolutional Neural Network, and the traditional Machine Learning of Support Vector Machine (SVM). The model leverages CNN capability for feature extraction and SVM for classification on the SOCOFing public dataset. The hybrid system achieved 99.25% accuracy. Nonetheless, the author emphasised the need for additional optimization and evaluation on diverse datasets for wider generalisation.

2.1. Research gap

Although several studies have leveraged traditional machine learning capabilities to determine gender using fingerprint images. Limited attention has been given to the potential power of Deep Learning Techniques and the high-performance power of pre-trained models such as ResNet, EfficientNet, or DenseNet on the SOCOFing datasets. Existing studies used older pre-trained models without data pre-processing and fine-tuning. This study is proposing an implementable model that compares CNN pre-trained architectures with other state of the art models using the SOCOFing dataset and evaluates their performance in fingerprint-based gender classification.

3. Materials and methods

3.1. Subjects

A biometric fingerprint database designed for academic research purposes called Sokoto Coventry Fingerprint (SOCOFing) dataset was collected from 600 African subjects. 600 subjects each having 10 files representing their 10 fingerprints was used for this study. Male finger prints consist of 4,832 (79.6%) while the female fingerprints contain 1,238 (20.4%) with age range between 18-65. The Figure 2 shows the sample input fingerprints

Figure 2 Sample Input fingerprints

3.2. Data pre-processing

The SOCOFing dataset requires systematic pre-processing to prepare its 55,273 fingerprint images for analysis. The pipeline for processing the dataset began with metadata extraction from filenames, capturing demographics, finger positions, and three alteration types. Image pre-processing involves intensity normalization to scale pixel values, which range from 0 to 1, contrast enhancement using histogram equalization to improve the visibility of the ridges, and also noise reduction through Gaussian filtering. Advanced processing techniques performed included orientation field estimation to map ridge directions and Gabor filtering for frequency-based improvement. Data splitting follows subject-wise combination to prevent mix-up, ensuring all fingerprints from one subject remain in the same train, validation and test split. Data augmentation techniques such as rotation, flipping, translation, and contrast adjustments were done to improve model robustness. For altered fingerprints, specialized handling addresses different difficulty levels and alteration types, with potential reconstruction for obscured regions. The processed output organizes images into standardized tensors with comprehensive metadata, which makes it ready for ML algorithms for processing of gender classification, fingerprint recognition, or alteration detection. This structured approach ensures data quality while maintaining the biometric integrity essential for reliable research outcomes. Data balancing was done using down sampling the male and female sets to 1,000 samples each.

3.3. Model architecture

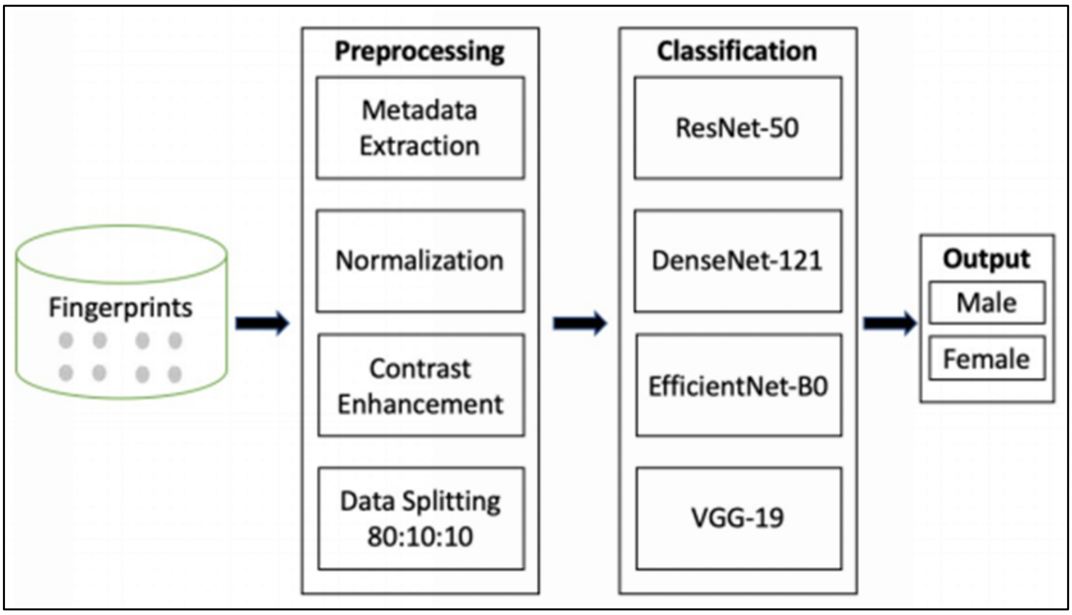

Figure 3 Model Architecture

3.4. Model development

In this research we employed deep learning-based models to perform gender classification. The dataset was split into ratio 80:10:10 for the training, validation and testing set respectively. That implies that for 1,000 males, we randomly split to 800 for training, 100 for validation, and 100 for testing. The same was repeated for females. So, a total of 1,600 data was used for training, 200 for validation, and 200 for testing. The training set was used to build the Residual Network 50 (ResNet50) Model, Dense Convolutional Network 121 (DenseNet121) Model, Efficient Convolutional Neural Networks (EfficientNet-B0) Model, and Video Geometry Group 19 (VGG19) Model, while the validation and testing sets were used in the model evaluation.

The core Convolutional Operation is described as:

$$y_{i,j}^{(k)} = b^{(k)} + \sum_{c=1}^{C} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} W_{m,n}^{(k,c)} \cdot x_{i+m,j+n}^{(c)} \quad \text{.................................} \quad (1)$$

x: input feature map
W: convolution kernel (filter)
b: bias
c: input channel
k: output channel
M,N: kernel size
y: output feature map

Visual Geometry Group (VGG) is a powerful CNN architecture that was introduced in 2014 in University of Oxford. It ensures a steady and high-accuracy result in prediction problems [32]. The VGG expression can be written as:

$$h^{(l)} = \sigma\left(\sum_{c} \sum_{m,n} W_{m,n,c}^{(l)} \cdot h_{i+m,j+n,c}^{(l-1)} + b^{(l)}\right) \quad \text{.................................} \quad (2)$$

3.5. Residual Networks (ResNet)

It was proposed by Microsoft Research, which introduced a residual block to address the challenge of vanishing gradient [22]. It has two connections, the first connection is allowed when the input and output have same dimensionality, and the second connection is used when the dimension of the image is increased [32]. The expression is presented as:

$$h^{(l)} = F(h^{(l-1)}) + h^{(l-1)} \quad \text{...} \quad (3.1)$$

Where F(.) is:

$$F(h) = \sigma\left(\sum_{c} \sum_{m,n} W_{m,n,c} \cdot h_{i+m,j+n,c} + b\right) \quad (3.2)$$

Combined:

$$h^{(l)} = \sigma\left(\sum W \cdot h^{(l-1)}\right) + h^{(l-1)} \quad (3.3)$$

3.6. Densely Connected Convolutional Network (DenseNet)

DenseNet CNN architecture, released in 2017 with its efficient use of parameters, and high accuracy on sizeable dataset, is presented as:

$$h^{(l)} = H^{(l)}\left(\left[h^{(0)}, h^{(1)}, \ldots\ldots, h^{(l-1)}\right]\right) \quad (4.1)$$

Expanded:

$$h^{(l)} = \sigma\left(\sum_{k=0}^{l-1} \sum_{c} \sum_{m,n} W^{(l,k)}_{m,n,c} \cdot h^{(k)}_{i+m,j+n,c}\right) \quad (4.2)$$

3.7. Efficient Networks (EfficientNet)

EfficientNet CNN architecture uses a compound coefficient that scale all the depth, width and resolution dimensions at the same time [22]. The expression is formulated as:

$$y = \sum_{c} \sum_{m,n} W_{m,n,c} \cdot x_{i+m,j+n,c} \quad (5.1)$$

Depth: $d = \alpha^{\phi}$, $Width\colon w = \beta^{\phi}$, $Resolution\colon r = \gamma^{\phi}$

Subject to:

$$\alpha \cdot \beta^{2} \cdot \gamma^{2} \approx 2 \quad (5.2)$$

During the modelling, we experimentally tuned the hyper-parameters like epochs and learning rates on the training. We evaluated our models using Sensitivity, Specificity, accuracy, F1-Score, and AUROC.

4. Results

4.1. Subjects

After introducing the down-sampling techniques, and to have a well-balanced dataset prepared for our algorithm, we had 1,000 for each class, out of which each subject has 10 files, and we considered 100 subjects.

4.1.1. Tools Used

This configuration establishes a specialized computing environment for fingerprint image analysis and deep Learning model development on Google Colab. Google Colab is a cloud-based Linux platform, offering GPU usage, confirmed by the CUDA-enabled PyTorch version (2.0.8+cu118). The basic data science stack is modern and powerful, using Python 3.11.12 with NumPy 2.0.2 and Pandas 2.2.2 for efficient numerical computation and data handling. This is essential for managing large datasets of fingerprint images and extracted feature vectors. Scikit-learn 1.6.1 provides a toolkit for ML tasks, such as prediction and classification based on fingerprint minutiae.

The environment is optimized for deep learning in computer vision. PyTorch serves as the framework for feature extraction and training Convolutional Neural Networks (CNNs) tailored for fingerprint gender classification. This was combined with Matplotlib for visualization. This setup is perfect for a fingerprint processing and pre-processing pipeline, from image loading and augmentation to model training and evaluation.

4.1.2. Classification Results

Evaluation Metrics for ResNet50, DenseNet 121, EfficientNetB0, and VGG19 can be found in Table 1.

Table 1 Evaluation Metrics of Deep Learning Fingerprint Gender Classification Models

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 Score (%)	AUC (%)
ResNet50	74.37	74.37	74.38	74.23	81.74
DenseNet121	68.75	68.75	68.75	68.39	75.21
EfficientNet-Bo	74.69	74.69	74.69	74.63	82.79
VGG19	68.44	68.44	68.44	67.55	76.91

The confusion matrix for ResNet50 can be seen in Figure 4, and the AUC of the 4 models can be found in Figure 8

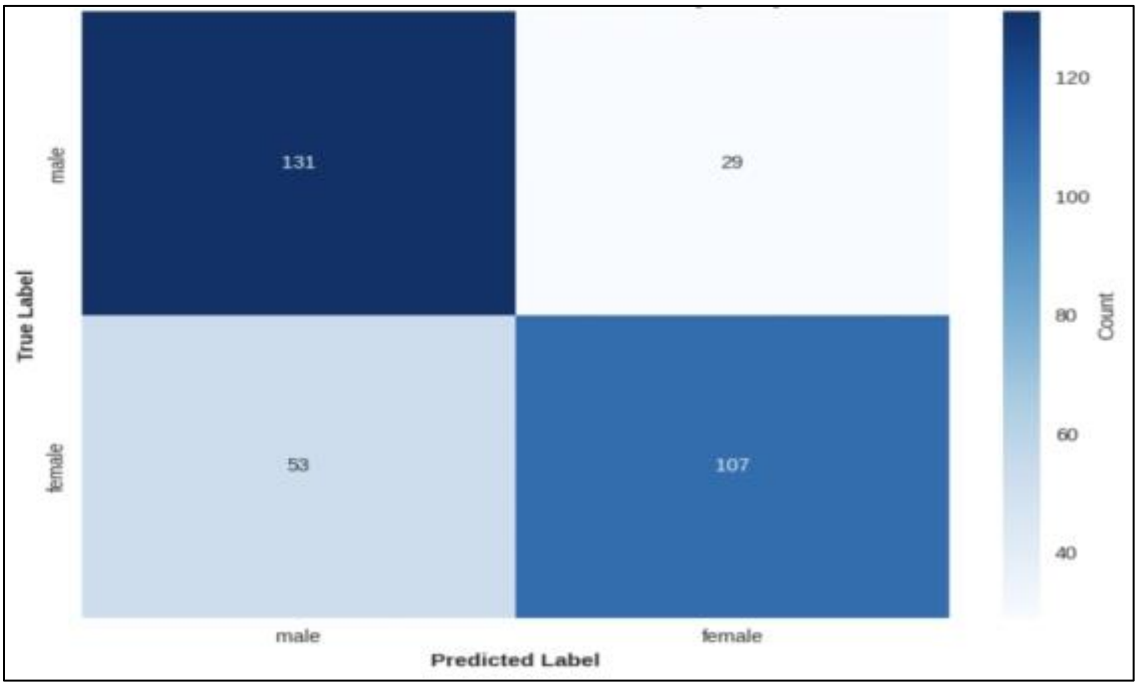

Figure 4 Confusion Matrix of the ResNet50 Model

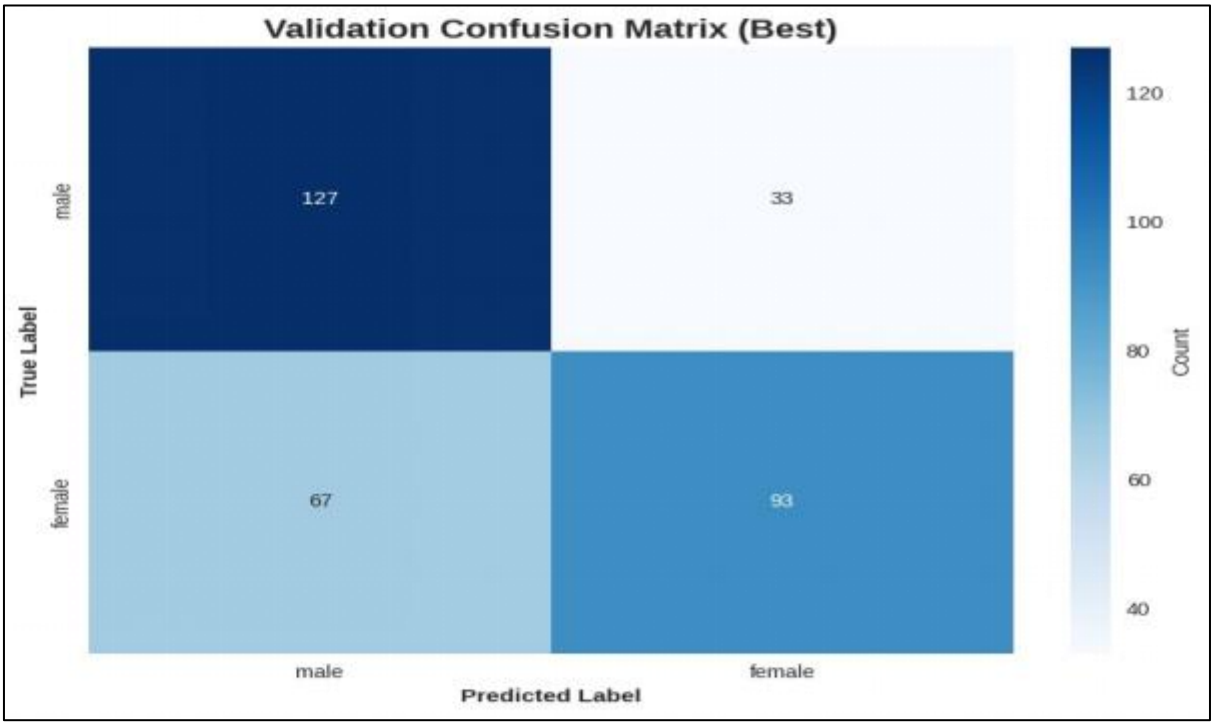

Figure 5 Confusion Matrix of the DesNet121 Model

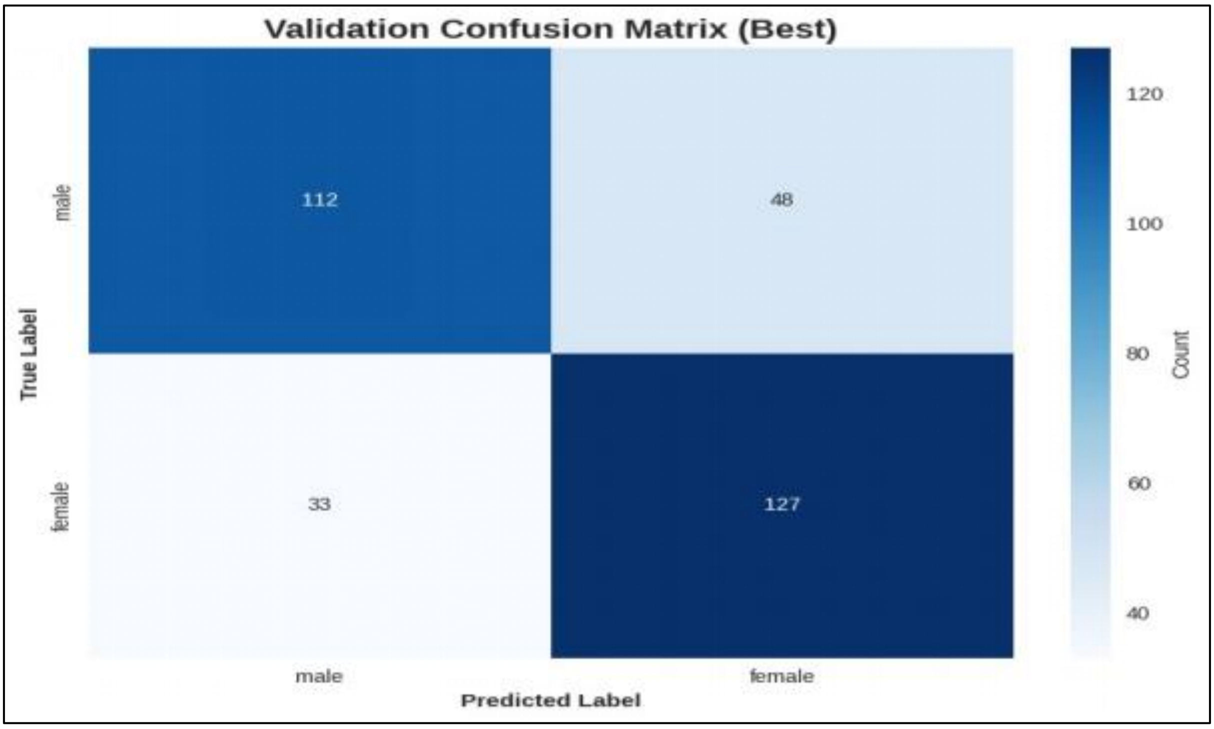

Figure 6 Confusion Matrix of the EfficientNetB0 Model

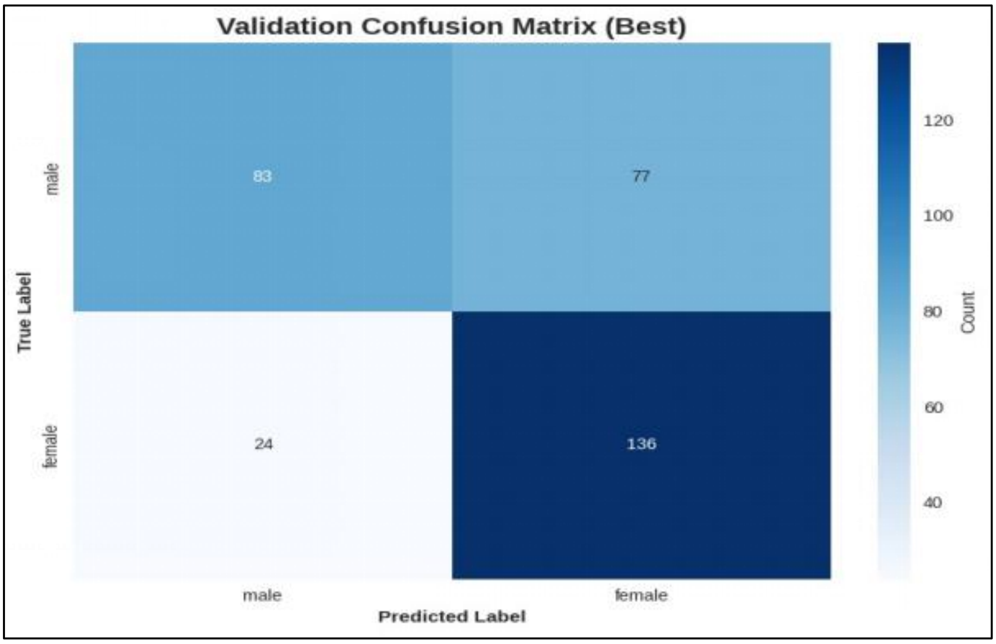

Figure 7 Confusion Matrix of the VGG19 Model

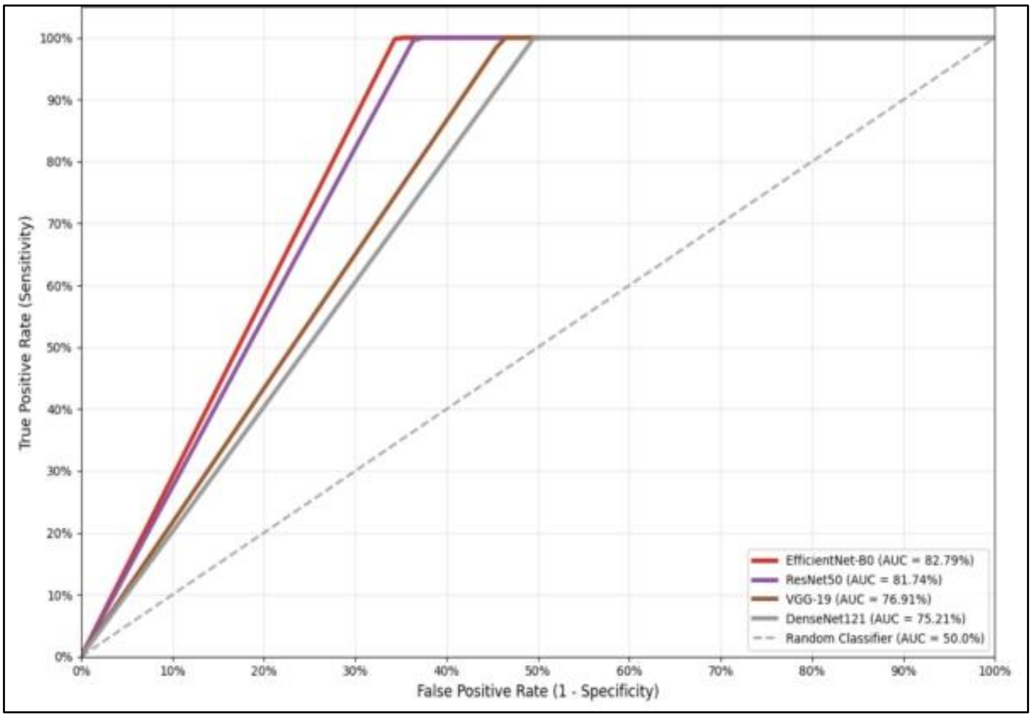

Figure 8 Area under the Curve of ROC

5. Discussion

This research aimed to classify gender using fingerprints. We achieved this by downloading a dataset from the SOCOFing dataset from Kaggle, an online repository. We used pre-processing techniques such as cropping, resizing and rotation, and balanced the dataset with down sample technique. We split the dataset into ration 80:10:10 for training, validation, and testing sets, respectively. We also fine-tuned the models using different batch sizes, epochs, and learning rates. We employed four different transfer learning models, which are ResNet50, DenseNet121, EfficientNet-Bo and VGG19, respectively.

The comparative analysis of the four deep learning architectures for fingerprint gender classification reveals significant performance variations, with EfficientNet-B0 performing best while VGG19 performed worst. This performance hierarchy provides information about the importance of architectural design and its impact on a model's capability for this specific gender classification task.

EfficientNet-B0 achieves the highest performance across all metrics, with 74.69% accuracy, sensitivity, and specificity, complemented by a 74.63% F1 score and the highest AUC of 82.79%. This best performance of EfficientNet can be attributed to EfficientNet's compound scaling method, which optimally balances network depth, width, and resolution. The models use efficient feature extraction while maintaining computational economy. This architectural efficiency appears to be suitable for fingerprint patterns, where subtle ridge characteristics and minutiae points may contain gender-related bio-markers.

ResNet50 showed nearly equivalent performance to EfficientNet-B0, achieving 74.38% accuracy with identical sensitivity and specificity scores of 74.37%. The 81.74% AUC indicates strong classifying capability, though slightly inferior to EfficientNet. ResNet's residual learning framework effectively addresses vanishing gradient problems in deep networks, allowing the model to learn complex fingerprint representations. The close competition between ResNet50 and EfficientNet-B0 suggests that both architectures successfully capture the relevant features in fingerprint patterns.

The performance gap becomes more pronounced with DenseNet121 and VGG19, which both achieve approximately 68.75% and 68.44% accuracy respectively. DenseNet's feature reuse through dense connectivity, may not be useful for fingerprint analysis because introducing redundant features does not contribute to gender classification. The 75.21% AUC for DenseNet121, indicates reduced classification confidence compared to the ResNet50 and EfficientNet-B0. The position of VGG19 as the least performing model showed the limitations of traditional convolutional architectures for this task. Though it has proven track records in general image classification experiments, but less effective for general feature extraction, and this makes it lack the specialized operations needed to capture fingerprint features.

The consistent equality between sensitivity and specificity across all models indicates balanced performance across gender classes, suggesting that the datasets were well-balanced and the models learned to recognize both male and female fingerprint patterns without significant bias. The AUC scores, all above 75%, confirm that all architectures possess meaningful discriminative power, though with varying degrees of confidence.

Our work is in line with the works of [6], who achieved the best accuracy of 97.89%, 69.86% and 63.05% for training, validating, and testing, respectively, with VGG-19, ResNet-50, and EfficientNet-B3. Our EfficientNet algorithm, which is our best model, outperformed their model by 4.83%.

The findings also showed that model complexity alone does not guarantee performance, as demonstrated by the result of VGG19 despite its extensive parameter count. The generalizability of the model is also a problem since the model was built on a dataset based on a single geographical location.

6. Conclusion

This comprehensive evaluation of Deep Learning Models for fingerprint-based gender classification showed that architecture impacts performance of the model. EfficientNet-B0 emerges as the best model, obtaining the best results across all metrics with 74.69% accuracy and 82.79% AUC, closely followed by ResNet50. This superiority showed the importance of efficient neural architecture design and compound scaling in capturing fingerprint patterns.

The significant performance gap between EfficientNet, ResNet, and VGG19 showed us the limitations of other models used for this biometric classification task. The consistent balance between sensitivity and specificity across all models indicates robust learning without gender bias, while the strong AUC scores confirm meaningful classification capability.

This research established a benchmark for future research in forensic biometrics and gender identification. The demonstrated efficacy of deep learning approaches opens promising avenues for non-invasive gender classification in security, forensic investigation, and anthropological studies. Also, the age range used in this study will make this model reliable and generally acceptable. Future research should explore ensemble methods combining EfficientNet and ResNet models, hoping to push the accuracy beyond 75%.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest, no research grants from any research body for this paper. The paper was sent for publication with the consent of all the authors.

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