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# Deep Learning Method for Multi-Attribute Analysis of Fingerprint Images

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**Abstract**

Estimation of gender, hand, and finger to minimize the probable suspects list in a fingerprint database search is a very important stride in forensic anthropology. Previous research attempted to estimate the gender, hand, and finger from the fingerprint, but the results were not consistent. In this effort, we proposed gender, hand, and finger estimation based on fingerprints using a deep convolution neural network. The publicly available SOCOFIG dataset which embraces 55222 no of fingerprints, is used for training and evaluation of the proposed procedure. On the aforementioned dataset, the suggested mode of operation achieves 99.38% gender, 99.46% hand, and 97.36% finger prediction validation accuracy. The results are competitive and commendable when compared to the preceding techniques.

**Keywords:** Biometric, Fingerprint, CNN, Gender Estimation, Hand Estimation, Finger Estimation.

**MSC 2020:** 68T07

**ACM CCS 2020:** I.5.1

## 1 Introduction

In today's environment of growing relevance for security and organization, identification and authentication procedures have emerged as a critical technology. The human visual system is self-sufficient and excellent in distinguishing human demographic characteristics like age, gender, voice, accent, etc. [1]. For instance, a youngster can distinguish between a parent by birth without having any prior knowledge of gender. On the other hand, computer systems are not clever enough to



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perform these kinds of jobs, therefore automatic personal recognition is important for the development of many applications, such as surveillance, vaccination, target advertising, content-based indexing and retrieval, etc. [2]. The method of identifying someone using behavioural or physiological features is known as biometric estimation [3]. Biometric identifiers [4] include things like fingerprints, facial patterns, speech patterns, and typing cadence [5]. Each of these markers is viewed favourably by the individual, and they can be combined to increase the precision of estimation proof [6]. One of the most advanced biometric technologies, fingerprints are accepted as valid forms of proof in courts of law all around the world because of their durability, universality, availability, and individuality [7] [8]. We can process a fingerprint's estimation, along with its gender, hand, and finger based on the variety of information that is accessible from the print [9].

In contemporary criminology, fingerprints are a critical component of forensic estimation. Currently, numerous computer tools, such as Automated Fingerprint estimation System (AFIS) [10], are used to compare the size, shape, and distinctive patterns associated with fingerprints. Gender, hand, and finger categorization from fingerprints is a crucial step in order to pinpoint a criminal and cut down on the number of suspects that need to be looked into [11]. The palmar and plantar surfaces of a finger are continually wrinkled and covered in tiny friction ridges [12] [13] [14]. All of the finger's friction ridges leave a print behind. The ridges that are thereby created during foetal development remain in place throughout an individual's lifetime until they are eliminated by skin decomposition after death [15].

Sir William Herschel employed the technique for the first time in India in 1858 to stop impersonation, but Sir Francis Galton is credited for systematising it for criminal estimation. In 1894, his approach was formally adopted in England, and Sir Edward Henry later made changes to it [16]. The use of fingerprints for gender, hand, and finger recognition, which will be more useful in narrowing down the suspects, has received less attention from researchers. In this proposed work, the objective is to identify gender, hand, and finger by using deep convolution network [17] and artificial neural network classifier on the enhancement of biometric estimation system by using the trait fingerprint. The organization of the manuscript is as follows: the previous literary work is reported in Section 2. The detailed proposed method and workflow is placed in Section 3. Section 4 contains the experimental result and performance analysis with discussion. Section 5 of the document contains concluding remarks.

# 2 Related Work

In the course of literary works, estimation of gender and hand with fingers was studied but to a limited extent. Researchers have not focussed much on the estimation of hand and finger from fingerprints rather they only focussed on gender detection. Nithin et al. [18] offer a study that tried to identify a certain region of Southern India's gender based on the number of finger ridges. Kaur et al. [19] used the

Table 1. Sokoto Coventry Fingerprint Dataset

| FINGERPRINT TYPE | COUNT | MALE | FEMALE | RIGHT HAND | LEFT HAND | INDEX | LITTLE | MIDDLE | RING | THUMB |
|---|---|---|---|---|---|---|---|---|---|---|
| REAL | 6000 | 4770 | 1230 | 3000 | 3000 | 1200 | 1200 | 1200 | 1200 | 1200 |
| ALTERED EASY | 17931 | 14266 | 3665 | 8978 | 8953 | 3588 | 3588 | 3588 | 3585 | 3582 |
| ALTERED MEDIUM | 17067 | 13641 | 3426 | 8679 | 8388 | 3459 | 3427 | 3412 | 3401 | 3368 |
| ALTERED HARD | 14272 | 11526 | 2746 | 7381 | 6891 | 3084 | 2904 | 2848 | 2720 | 2716 |
| TOTAL | 55270 | 44203 | 11067 | 28038 | 27232 | 11331 | 11119 | 11048 | 10906 | 10866 |

Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), and Power Spectral Density (PSD) for fingerprint analysis; and then categorization is performed. A dataset of 220 people of various ages and genders has been compiled. The frequency domain computation is done using a predetermined threshold, which ultimately determines the gender. The overall recognition rate for males and females, respectively, is 79.07% and 90%. Gnanasivam et al. [20] did a study to determine the gender from fingerprints based on the quantity of prints and the size of the fingertips. They recommended employing the Optimal Rating Allocation method to obtain the highest results for men and women using a fingerprint database that was domestically produced. The gender of the fingerprints collected by the scanner from four age groups was determined by counting the quantity of ridges between the center to the delta. Their approach had a success percentage that ranged from 84.1% to 90.11%. Based on a dataset of 100 fingerprints, a KNN classifier was used by Gour et al. [21] to combine characteristics such as the discrete wavelet and discrete cosine transformation approach over a small number of photos, yielding an accuracy of 90%. Falohun et al. [22] built a system that uses discrete wavelet transformation on 280 fingerprint photos and is trained using a back-propagation neural network. This system achieved a classification accuracy of 80%. Gornale et al. [23] used the Haralick texture descriptor on a dataset with 740 fingerprint photos, and the system's performance was reported to be 94% effective. Gornale et al. [24] further used local binary pattern features on a dataset of 740 fingerprint images and further attained a 95.8% accuracy by utilizing the KNN classifier. Jain et al. [25] suggested an approach to locate frequency domain vector using 2D-DWT, and the features of the non-zero singular values are extracted using SVD. The gender of a fingerprint is classified using the K-NN classifier. A collection of Hundred left-hand index fingerprints of 50 males as well as 50 girls within the same age bracket was used to evaluate the suggested approach, and it had an accuracy rate of over eighty percent. Wadhwa et al. [26] suggested a method for identifying a person's gender that was centered on RVA and DCT coefficients. The ridge with valley area, entropy, along with RMS value of the DCT coefficients of a fingerprint are used to classify age and gender. Anjikar et al. [27] proposed a technique for gender classification using fingerprint pictures. Preprocessing techniques including scaling, filtering, including thresholding are used on each image. This was followed by the use of Unit Dependent Discrete Cosine Transformation, that separates each picture into discrete blocks and gathers coefficient characteristics from each block. The K-Nearest method was used to classify data using this feature set in order to distinguish between male and female fingerprints, Abdullah et al. [28] used global parameters such as ridge density, ridge thickness to valley ratio (RTVTR), and the number of white lines are extracted. The perceptron-based multilayer neural network is then given these global descriptors. Rattani et al. [29] estimated gender using fingerprints, evaluation of various textural descriptors including Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Local Phase Quantization, and Binarized Statistical Image Features were provided.

# 3 Proposed Method

## 3.1 Dataset

The proposed method uses the publicly available dataset called Sokoto Coventry fingerprint dataset [30] [31] for training and testing. The complete dataset comprises 6000 genuine fingerprint photos that have been altered using the three types of alteration procedures, central rotation, z cut, along with obliteration to create 17931 easy, 17067 medium, and 14272 difficult altered images that together provide an altogether of 55270 fingerprints. Table 1 has a thorough description of the database. Some of the example images from the collection are shown in Figure 1.

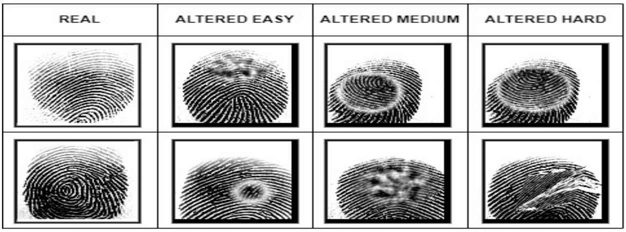



Figure 1. Sample of Dataset SOKOFIG

## 3.2 Preprocessing

The original dataset has been pre-processed as per the need of the proposed algorithm. All the input images are resized to $96 \times 96$ resolution from $96 \times 103$ (as in the original) and converted into the corresponding binary images before feeding to the proposed model for training and testing. Three sets have been created from the entire dataset. A total of 14781 images were utilized for testing, 10347 images – for validation, and 24142 images – for training.

## 3.3 Implementation Methodology:

The proposed method implementation steps are discussed in details with its working model, network architecture, and the Training process.

### 3.3.1 Work flow:

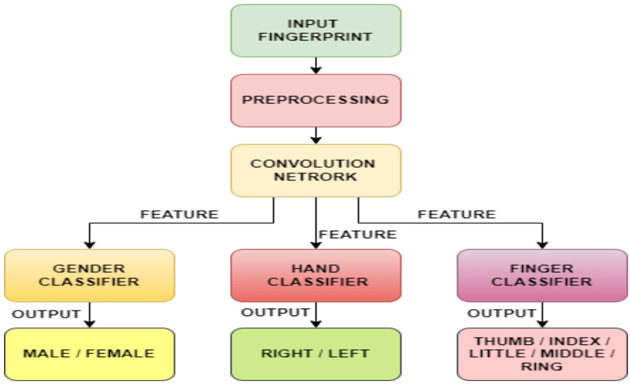



Figure 2. Proposed Method Work Flow

At first, the pre-processed image set is passed through a convolutional network for extracting salient features. The obtained features are subsequently fed into 3 parallel artificial neural network classifiers dedicated to detecting gender, hand, and finger respectively. Figure 2 shows the work flow for the suggested technique.

### 3.3.2 Network Architecture

Feature extraction from the input fingerprint images is implemented with 5 layers of convolution followed by Maxpooling and batch normalization. A global Maxpooling operation is executed at the end to obtain the fine-tuned feature set The extracted features are then passed to three different artificial neural network classifiers having the number of nodes 128, 128, and 256 by which gender, hand, and finger are identified, respectively. The advocated network's structure is depicted in Figure 3.

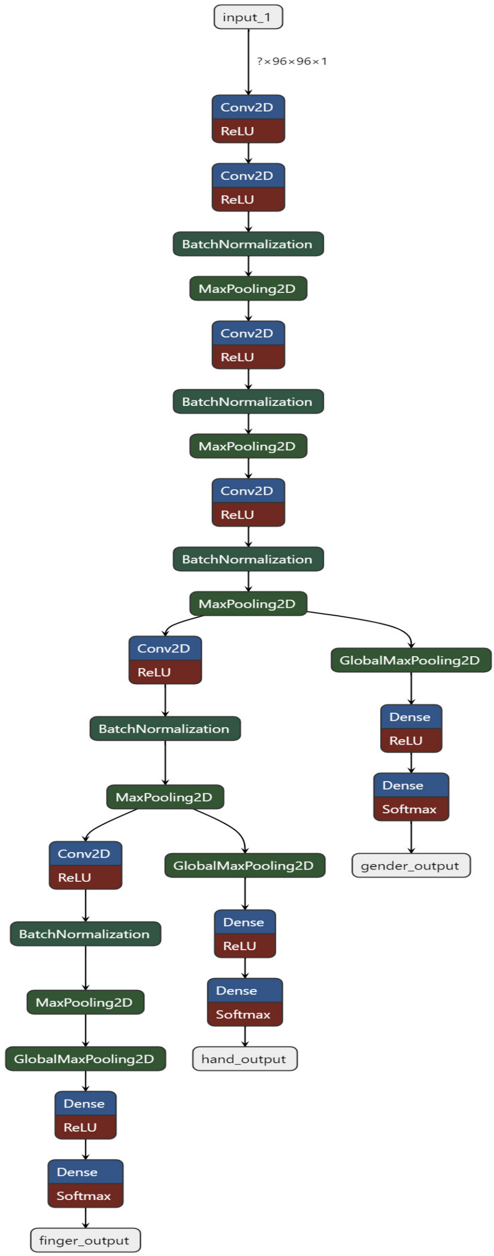



Figure 3. Network Architecture

### 3.3.3 Network Parameters

The 2D convolution is performed using the following equation:

$$\Omega * F(p,q) = \left( \sum_{\delta p=-k_i}^{k_i} \sum_{\delta q=-k_j}^{k_j} \omega(\delta p, \delta q) \cdot F(p+\delta p, q+\delta q) \right) + \Omega_{\text{bias}} \, . \quad (1)$$

The activation function used in the convolution network is the Rectifier Linear Unit which can be represented with the following equation:

$$R(z) = \left\{ \begin{array}{cc} z & z > 0 \\ 0 & z <= 0 \end{array} \right\} . \quad (2)$$

In the artificial neural network classifier, the activation function used is SoftMax and can be represented with the following formula:

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} . \quad (3)$$

The loss function which has been optimized in the network is categorical cross entropy and represented by the following formula:

$$CE = -\log \left( \frac{e^{s_p}}{\sum_j^C e^{s_j}} \right) . \quad (4)$$

The uniform initializer has been employed for initial weight assignment of the network. Equation 5 represents the mathematical notation:

$$\mathrm{Var}\,(w_i) = \frac{2}{fan_{in}} . \quad (5)$$

With $stddev = sqrt(2/fan_{in})$, where $fan_{in}$ is the amount of input units, it pulls observations from a clipped normal distribution centered on 0.

### 3.3.4 Network Training

The network has undergone 50 epochs of training with a typical batch size of 32. The detail parameter list of the network is shown in Table 2.

Table 2. Parameter details of the proposed network

| Layer | Size | Parameter |
|---|---|---|
| InputLayer | [None, 96,96,1)] | 0 |
| Conv2D | (None, 94,94,32 ) | 320 |
| Conv2D | (None, 92, 92, 64) | 18496 |
| BatchNormalization | (None, 92, 92, 64) | 256 |
| MaxPooling2D | (None, 46,46,64 ) | 0 |
| Conv2D | (None, 44,44,96 ) | 55392 |
| BatchNormalization | (None, 44, 44, 96) | 384 |
| MaxPooling2D | (None, 22, 22, 96) | 0 |
| Conv2D | (None, 20,20,128 ) | 110720 |
| BatchNormalization | (None, 20,20,128 ) | 512 |
| MaxPooling2D | (None, 10,10,128) | 0 |
| Conv2D | (None, 8,8,160) | 184480 |
| BatchNormalization | (None, 8,8,160 ) | 640 |
| MaxPooling2D | (None, 4,4,160 ) | 0 |
| Conv2D | (None, 2, 2, 192) | 276672 |
| BatichNormalization | (None, 2, 2, 192) | 768 |
| MaxPooling2D | (None, 1, 1, 192) | 0 |
| GlobalMaxPooling2D | (None, 128) | 0 |
| GlobalMaxPooling2D | (None, 160) | 0 |
| Global MaxPooling2D | (None, 192) | 0 |
| Dense | (None, 128) | 16512 |
| Dense | (None, 128) | 20608 |
| Dense | (None, 512) | 98816 |
| Dense | (None, 2) | 258 |
| Dense | (None, 2) | 258 |
| Dense | (None, 5) | 2565 |

# 4 Performance Analysis of Experimental Findings

This section offers an examination of the suggested method's performance together with the experimental findings. Table3, Table4, and

Table5 show the accuracy, loss value of training, and validation for gender, hand, and finger, respectively.

Table 3. Training & Validation Accuracy and Loss for Gender

| Gender | Accuracy | Loss Value |
|---|---|---|
| Training | 99.94% | .0025 |
| Validation | 99.38% | .0229 |

Table 4. Training & Validation Accuracy and Loss for Hand

| Hand | Accuracy | Loss Value |
|---|---|---|
| Training | 99.89% | .0030 |
| Validation | 99.46% | .0189 |

Table 5. Training & Validation Accuracy and Loss for Finger

| Finger | Accuracy | Loss Value |
|---|---|---|
| Training | 99.73% | .0070 |
| Validation | 97.36% | .1201 |

A sample output of the proposed network is shown in Fig4.

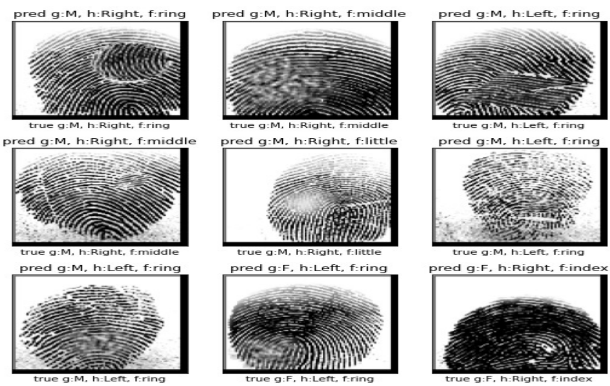



Figure 4. Sample output of The Proposed Model

Table 6 compares fingerprint gender categorization to contemporary methodology.

Table 6. Comparison of the Precision of Fingerprint Gender Determination

| **Methods** | **Technique** | **Precision** |
|---|---|---|
| Method of [32] | Neural Network | 87.64% |
| Method of [33] | Support Vector Machine | 88% |
| Method of [34] | K-Nearest Neighbors | 88.28% |
| Method of [35] | Back Propagation Artificial Neural Network | 91.45% |
| Method of [36] | Gaussian Mixture Model | 92.67% |
| Method of [37] | Naive Bayes | 95.3% |
| Method of [38] | Convolution Neural Network | 75.2% |
| Method of [39] | Convolution Neural Network | 62.35% |
| Method of [40] | Convolution Neural Network | 91.3% |
| Method of [41] | Convolution Neural Network | 87% |
| **Proposed Method** | **Convolution Neural Network** | **99.38%** |

The provided Table 6 presents a comparative analysis of different methods used for fingerprint gender determination, focusing on their precision rates and employed techniques. Various approaches, such as Neural Networks, Support Vector Machines, K-Nearest Neighbours, and Gaussian Mixture Models, among others, have been employed by different studies to determine gender from fingerprints. Notably, some studies report high precision rates, with Naive Bayes classification achieving a precision of 95.3%. However, there are also instances where precision rates are comparatively lower, such as the Convolution Neural Network (CNN) techniques reported by Shehu et al. [38] and Terhorst et al. [39], with precision rates of 75.2% and 62.35% respectively. Conversely, the proposed method utilizing a CNN demonstrates a significantly higher precision rate of 99.38%, indicating its superior performance in capturing intricate fingerprint patterns for accurate gender determination. This suggests the importance of utilizing advanced techniques like CNNs to enhance precision rates in fingerprint-based gender determination.

Table 7. Comparison of suggested procedure with the existing latest practices for Hand identification

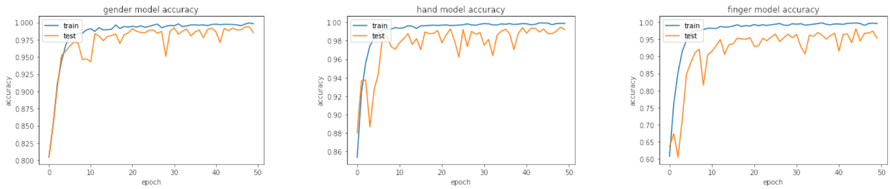
| Sl No. | Methods | Technique | Precision |
|---|---|---|---|
| 1 | Method in [38] | ConvNet | 93.5% |
| 2 | **Suggested Method** | **ConvNet** | **99.46%** |

Table 8. Comparison of suggested procedure with the existing latest practices for Finger identification.

| Sl No. | Methods | Technique | Precision |
|---|---|---|---|
| 1 | Method in [38] | ConvNet | 76.72% |
| 2 | **Suggested Method** | **ConvNet** | **97.36%** |

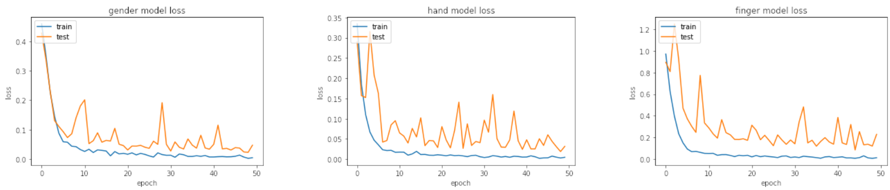
As not many researchers have studied the detection of hand and finger from fingerprint, the provided Tables 7 anf 8 offer a comparative analysis between the suggested procedures and the existing latest practices for hand and finger identification, respectively. In the first table, the existing method proposed by Shehu et al. [38] achieves a precision rate of 93.5% using Convolutional Neural Networks (ConvNet). In contrast, the suggested method demonstrates a significantly higher precision rate of 99.46% using the same ConvNet technique. Similarly, in the second table, the existing method for finger identification, also proposed by Shehu et al. [38], achieves a precision rate of 76.72%, while the suggested method yields a substantially improved precision rate of 97.36% using ConvNet. These findings suggest a significant enhancement in precision rates with the suggested methods compared to the existing practices, particularly in finger identification. The utilization of ConvNet techniques appears to be effective in improving precision rates in both hand and finger identification tasks. Such advancements are crucial in enhancing the reliability and accuracy of biometric identification systems, potentially leading to more robust security measures and efficient authentication processes in various domains.

Fig 5 and Fig 6 are illustrating the accuracy and loss function plot for gender, hand, and finger, respectively, during training and validation.




(a) Gender (b) Hand (c) Finger

Figure 5. Accuracy Curve of Training & Validation




(a) Gender (b) Hand (c) Finger

Figure 6. Loss Curve Training & Validation

The combined training and verification loss of the complete network is shown in Fig. 7.

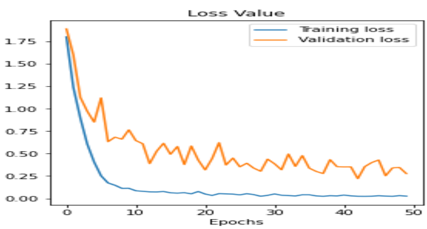
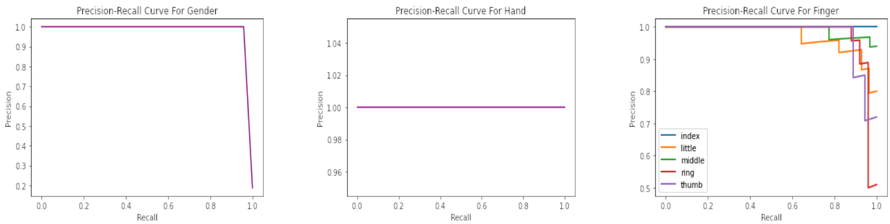


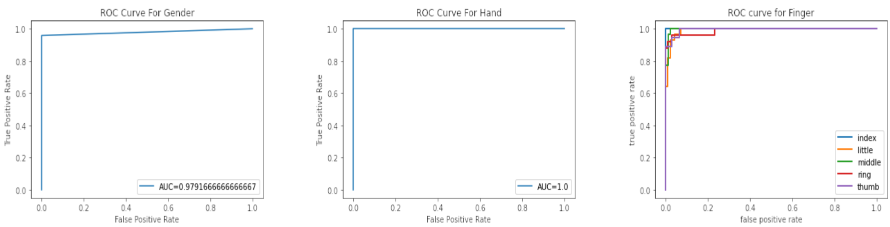

Figure 7. Over All Training & Validation Loss For Model

Fig8 and Fig9 show the precision-recall and ROC curve plot of gender, hand, and finger, respectively.




(a) Gender (b) Hand (c) Finger

Figure 8. Precision-Recall Plot




(a) Gender (b) Hand (c) Finger

Figure 9. ROC Plot

Table9, Table10, and Table11 represent the classification report for gender, hand, and finger, respectively.

Table 9. Gender Categorization Classification Details

| | **Precision** | **Recall** | **F1-Score** | **Support** |
|---|---|---|---|---|
| **Male** | 0.99 | 1.00 | 1.00 | 104 |
| **Female** | 1.00 | 0.96 | 0.98 | 24 |
| **Accuracy** | | | 0.99 | 128 |
| **Macro Average** | 1.00 | 0.98 | 0.99 | 128 |
| **Weighted Average** | 0.99 | 0.99 | 0.99 | 128 |

Table 10. Hand Categorization Classification Details

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| **Right** | 1.00 | 1.00 | 1.00 | 65 |
| **Left** | 1.00 | 1.00 | 1.00 | 63 |
| **Accuracy** | | | 1.00 | 128 |
| **Macro Average** | 1.00 | 1.00 | 1.00 | 128 |
| **Weighted Average** | 1.00 | 1.00 | 1.00 | 128 |

Table 11. Finger categorization Classification Details

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| **Thumb** | 1.00 | 1.00 | 1.00 | 26 |
| **Middle** | 1.00 | 1.00 | 1.00 | 29 |
| **Index** | 1.00 | 0.96 | 0.98 | 25 |
| **Ring** | 1.00 | 0.96 | 0.98 | 24 |
| **Little** | 0.92 | 1.00 | 0.96 | 24 |
| **Accuracy** | | | 0.98 | 128 |
| **Macro Average** | 0.98 | 0.98 | 0.98 | 128 |
| **Weighted Average** | 0.99 | 0.98 | 0.98 | 128 |

Table 12. Statistical Measures of The Proposed Model

| Parameter | Formula | Gender | Hand | Finger | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | Thumb | Index | Middle | Ring | Little |
| Sensitivity | tp / (tp + fn) | 0.9905 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| Specificity | tn / (fp + tn) | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.9905 | 0.9811 |
| Precision | tp / (tp + fp) | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.9583 | 0.9231 |
| Negative Predictive Value | tn / (tn + fn) | 0.9583 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| False Positive Rate | fp / (fp + tn) | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0095 | 0.0189 |
| False Discovery Rate | fp / (fp + tp) | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0417 | 0.0769 |
| False Negative Rate | fn / (fn + tp) | 0.0095 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Accuracy | (tp + tn) / (tp + tn + fp + fn) | 0.9922 | 1.0 | 1.0 | 1.0 | 1.0 | 0.9922 | 0.9846 |
| F1 Score | 2tp / (2tp + fp + fn) | 0.9952 | 1.0 | 1.0 | 1.0 | 1.0 | 0.9787 | 0.9600 |
| Matthews Correlation Coefficient | (tp x tn − fp x fn) / (sqrt((tp + fp) x (tp + fn) x (tn + fp) x (tn + fn))) | 0.9743 | 1.0 | 1.0 | 1.0 | 1.0 | 0.9743 | 0.9517 |

The different statistical measures depending on the classification report of the proposed model are tabulated in Table 12, where tp stands for true positive, tn stands for true negative, fp stands for false positive, and fn stands for false negative. Let's delve into the analysis of each parameter:

- **Sensitivity:** Sensitivity is a measurement of the proportion of accurately detected positive instances as well as the real positive rate. Across all attributes (gender, hand, and fingers), sensitivity scores are remarkably high, ranging from 0.9905 to 1. This indicates that the model is effective in correctly identifying the specified attributes.

- **Specificity:** Specificity quantifies the true negative rate and represents the proportion of correctly identified negative cases. Once again, the model achieves perfect specificity scores (1.0) for most attributes, indicating its ability to accurately identify negative cases.

- **Precision:** Out of all anticipated positive instances, precision calculates the percentage of true positive cases. Similar to sensitivity and specificity, the precision scores are generally high, with perfect precision achieved for most attributes.

- **Negative Predictive Value:** The percentage of actual negative instances vs all expected negative cases is represented by the negative predictive value. As with other metrics, the model demonstrates high accuracy in predicting negative cases, resulting in scores close to 1 for most attributes.

- **False Positive Rate:** The percentage of wrongly projected positive instances out of real negative cases is represented by the term "False Positive Rate". Notably, the score is consistently low across all attributes, with values of 0.0, indicating that the model has a very low false positive rate.

- **False Discovery Rate:** The percentage of wrongly anticipated positive instances out of all projected positive cases is measured by the false discovery rate. Again, the score is consistently low or zero, suggesting that the model has a high precision in predicting positive cases.

- **False Negative Rate:** The ratio of wrongly projected negative instances to real positive ones is known as the false negative rate.

Impressively, the score is consistently negligible (close to 0.0), indicating that the model rarely misses positive cases.

- **Accuracy:** By taking into account real positives, real negatives, false positives, along with false negatives, accuracy measures how accurately forecasts have generally turned out. The accuracy scores are exceptionally high, ranging from 0.9846 to 1.0, indicating the model's overall reliability in identifying the specified attributes.

- **F1 Score:**A fair evaluation of the model's performance is provided by the F1 Score, which combines precision and recall. The F1 scores are generally high, further highlighting the model's effectiveness in identifying the specified attributes accurately.

- **Matthews Correlation Coefficient:** The accuracy of classifications is gauged by the Matthews Correlation Coefficient. The scores are consistently high, close to 1, demonstrating the model's robustness in accurately classifying the specified attributes.

The analysis of the performance metrics reveals that the deep learning model performs exceptionally well in gender, hand, and finger estimation from fingerprint images. The model consistently achieves high accuracy, precision, and sensitivity scores while maintaining low false positive and false negative rates. These results indicate the model's potential for applications in biometrics, access control systems, and forensic investigations, where accurate attribute estimation is crucial.

Obtaining annotated fingerprint datasets, especially with gender, hand, and finger annotations, presents a significant challenge in biometric research. Limited availability of such datasets impedes the development and evaluation of fingerprint identification models. Currently, one of the most widely used annotated fingerprint datasets is the NIST Special Database 4. Despite its usefulness, this dataset remains scarce in terms of the annotations needed for comprehensive research. However, despite these challenges, the proposed model demonstrates promising results. Testing the proposed model on the NIST Special Database 4 reveals an impressive accuracy of 96%. This high accuracy underscores the effectiveness of the proposed model in fingerprint identification tasks, despite the scarcity of annotated datasets. The model's robust performance suggests its potential applicability in real-world scenarios, emphasizing the importance of continued research and innovation in the field of biometric identification.

In the realm of latent fingerprint analysis, challenges arise when dealing with images containing extensive background noise or only a partial representation of the fingerprint, where less than 40% of the image is present. In such cases, the performance of the model is notably affected, with accuracy dropping to 72%. This decline in accuracy underscores the limitations of the model when faced with incomplete or heavily distorted fingerprint images. It's important to note that the model was trained on a diverse dataset encompassing full images with varying levels of alteration, including small, medium, and high degrees of distortion. Despite the satisfactory accuracy achieved on these full images, the model's performance diminishes when confronted with latent fingerprints exhibiting significant background noise or partial representations. These findings highlight the importance of further research and development to address the challenges posed by latent fingerprints, particularly those with substantial background noise or partial image content, in order to enhance the accuracy and reliability of fingerprint identification systems. Figure 10 shows some examples of latent print where the model did not predict correctly.


Figure 10. Example of false-prediction on Latent Fingerprint by proposed model

# 5 Conclusion

In conclusion, the deep learning model developed for gender, hand, and finger estimation from fingerprint images has yielded exceptional accuracy results. With accuracy rates of 99.38% for gender estimation, 99.46% for hand estimation, and 97.36% for finger estimation, the model has demonstrated its robustness and effectiveness in accurately classifying these attributes from fingerprint data. The widespread use of anthropometric methods of estimation immediately decreased as a result of the revelation that fingerprints are uniquely identifiable, and which are later adopted as a more effective form of estimation. The most trustworthy and recognised form of evidence in a court of law today is without a doubt fingerprint data. Due to the enormous capacity of fingerprints being a trustworthy assessment tool, researchers are now investigating how fingerprints relate to a person's gender, hand, and finger. Results of gender classification utilizing these dominant traits showed that the suggested method can be a strong competitor for usage within forensic anthropology to reduce the number of probable suspects and offer a probable probability value for the suspect's gender, hand, and finger.

# 6 Future Scope

Our next research will compare this freshly developed algorithm to existing classifiers in order to raise its effectiveness rate and identify the best one for this proposed approach. We also desire to contrast our software, which makes use of the same data as the other classification algorithm, in order to evaluate the efficacy as well as the effectiveness of the offered ways. By integrating fingerprint features obtained by the layers of convolution with the minute points utilized in the layer that is completely linked, we will also aim to improve the classification of gender with fingers. This will also improve the categorization of hands and fingers. We'll also look at whether other factors, such as fingerprint thickness as well as valley thickness, may improve how well deep CNN models classify data.

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