

## Gender Classification Based on Fingerprint Analysis

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**Abstract:** Gender classification plays an active role in several applications such as biometrics, criminology, surveillance, human computer interaction, commercial profiling. Though biometric traits such as face, gait, iris and hand shape are used for gender classification in the past, majority of the work is based on face as it contains more prominent features than others. In this paper we have analyzed fingerprints for gender classification with a hope that it has great potential for future research. We have employed a three convolutional layer CNN with rectified linear (ReLU) and tanh activation functions on NIST database which contains a set of 4000 images and achieved 99% accuracy. Performance of the proposed system demonstrated that fingerprints contains vital features to discriminate gender of a person.

**Keywords:** Biometric, convolutional neural network (CNN), fingerprint, gender classification

### 1. Introduction

A fingerprint image is a pattern of ridges and valleys, with ridges are dark lines while valleys are light areas between the ridges. Its uniqueness is suitable for biometric authentication systems than others because fingerprints have advantages such as: feasible, differ from each other (distinct), permanent, accurate, reliable and acceptable. This can be used by anthropologists to classify gender from the fingerprints obtained from articles and by crime investigators to minimize the range of the suspects. Although fingerprints are one of the most mature biometric technologies and are considered as legitimate proofs of evidence in courts of law all over the world, relatively little machine vision method has been proposed for gender identification. Studies carried out so far in gender determination have used generally ridge related parameters such as fingerprint ridge count, ridge density, ridge thickness to valley thickness ratio, ridge width and fingerprint patterns and pattern types. Presently several application areas have embraced the fusion of features and synthesis to classifier, such as image recognition. Most of the available research on gender classification using fingerprints are based on the fingerprint patterns such as whorl, left loop, right loop, arch and tented arch shown in figure 1. These approaches have given insight about the ridge parameters but fails to give accurate measuring of the parameter.

#### 1.1. Arch

It is a wave-like pattern. An arch has friction ridges that enter on one side and cross to the other side while rising upward in the middle. There are two types of arches. They are plain which has no delta or core, and tented which has a delta in the center. Tented arches rise to a sharper point than plain arches.

#### 1.2. Loop

This fingerprint pattern enters and leave the same way. Two types of loops are available. Radial, which opens toward the thumb and Ulnar, which opens toward “pinky” (little finger).

#### 1.3. Whorl

A plain whorl has two deltas and at least one ridge making a complete circuit. It may be spiral, oval or any variant of the circle.

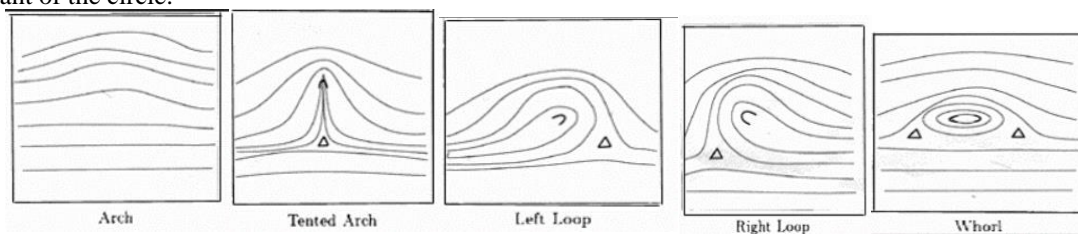


Figure 1. Fingerprint classes (a) Whorl (b) right loop (c) left loop (d) arch (e) tented arch

### 2. Related Works

S.F. Abdullah, and Z.A. Abas[1], proposed a multilayer perceptron neural network in classifying gender using fingerprint. The classification is achieved by extracting the fingerprint features from ridge thickness, ridge density to valley thickness ratio and white line count. This study found that women has a higher value in ridge thickness and ridge valley ratio. Emanuelamar as go [2] used quality and texture features to estimate age and gender from fingerprints. In this work they proposed a methodology to automatically infer age and gender from fingerprint images. In this classification model, texture of an image was captured using Local Binary Pattern(LBP) and Local Phase Quantization(LPQ) operators and achieved 89.1% accuracy.

Hazım Kemal Ekenel [3], have shown that generic and domain specific deep CNN models can be transferred successfully for age and gender classification problems. By using appropriate transfer learning approaches a pre-trained CNN model can perform even better than training a new task specific. Gil Levi and Tal Hassner [4], classified age and gender using CNN. They used a modern deep CNN. Their network was relatively modest due to the limited computational resources of the time and the algorithmic challenges of training bigger networks. They have resolved overfitting problem by deep convolutional neural network. Suman Sahu and prabakarrao[5], compared the result of neural network and adaptive neuro fuzzy inference system(ANFIS) result in determination gender using fingerprint. In this approach they used Discrete wavelet transform (DWT) to decompose the fingerprint image into a multi-resolution representation in order to keep the least coefficients possible without losing useful image information. They found that the resultant 2-D wavelet decomposition of an image such as low-low (LL), low-high (LH), high-low (HL), and high-high (HH) sub-bands represent different image properties. Mangesh K. and Shinde[6] analyzed fingerprint image for gender classification or identification using Wavelet Transform and Singular Value Decomposition. They verified, the performance of the proposed gender classification algorithm by using the internal database and summarized the success rate (in percentage) of gender classification using DWT, SVD and combination of both by a KNN classifier. S.S.Gornale, and Basavanna M [7] proposed a model for gender classification of fingerprints based on Support Vector Machines (SVM) with 10-cross validation technique. They divided the work into three sections, first is pre-processing of all fingerprint's images, second is computation of statistical features of Discrete wavelet transform and third is classification of testing fingerprints as male and female finger-prints using SVM classifiers with RBFsigma and Quadratic kernel function. All the above-mentioned models are not efficient as they require more computational time to train and validate the data. We have proposed a convolutional model for fingerprint gender classification.

### 3. Proposed work

In this paper, we have utilized Convolutional neural network (CNN) model for gender classification based on fingerprint images. It is a well-known model applied in numerous computer vision applications. In this work we exploit the unique ability of CNN to train a model to determine gender of the images from the fingerprint dataset. The CNN used in this work uses the construction shown in figure 2.

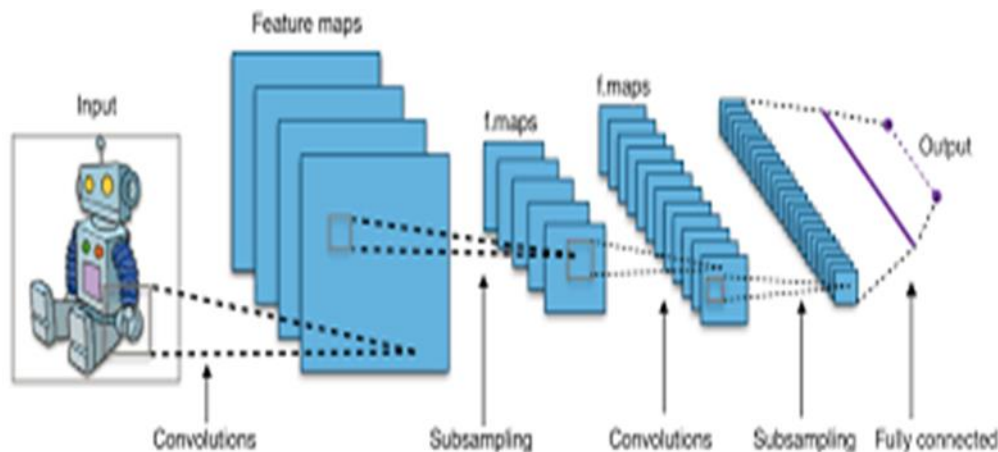


Figure 2. CNN Architecture

#### 3.1 Convolutional Layer

The most critical component in the model is the convolutional layer. This part aims at reducing the size of the image for faster computations of the weights and improve its generalization. The CNN model has three convolutional layers with 20 3x3, 40 3x3, 60 3x3, 80 3x3 filter kernels. Each convolutional layer consists of a bank of filters (weights) that are convolved with the output of the previous layer, or the input image if it is the first layer, to produce some response. The convolutional layers extract features from the input images. The first convolutional layer extracts low level features such as lines and edges and the higher-level layers extracts high level features. During the convolutional part, the network keeps the essential features of the image and excludes irrelevant noise. Moreover, the output of every convolutional layer is shaped by a rectifier linear unit (ReLU) function.

#### 3.2. Pooling Layer

The sub sampling layer is used to reduce the feature resolution. This layer reduces the number of connections between the convolutional layers, so it will reduce the computation time also. In each case, the input image is divided into non-overlapping two dimensional spaces. The input size is 4x4 and sub sampling size is 2x2. A 4x4 image is divided into four non-overlapping matrices of size 2x2. The max-pooling layer performs sub-sampling on the outputs generated by the previous convolutional layers by selecting the maximum value in an MxM window. In the case of min pooling, the minimum value of the four values is selected. Illustration of max pooling

and min pooling is shown in figure 3. By reducing the dimensionality, the network has lower weights to compute, so it prevents overfitting.

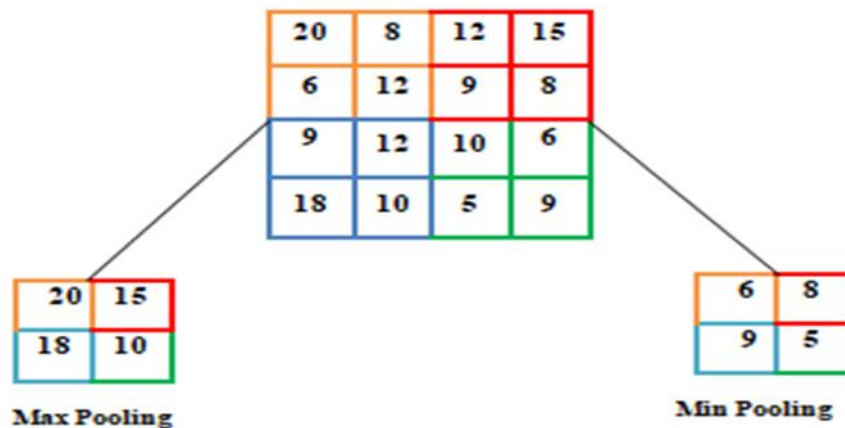


Figure 3. Process of Pooling Operations

### 3.3. Activation Function

The Activation Function is for improving the CNN performance. There are three familiar activation functions such as Sigmoid, Tanh and Relu. The performance of the standard activation function Relu has been compared with tanh activation function in this paper. Its role is to remove every negative value from the filtered images and replace it with zeros which is depicted in figure 4. The Relu activation function is defined as:

$$b_{i,j,k} = \max(a_{i,j,k}, 0)$$

Where,  $a_{i,j,k}$  is the input of the activation function at location (i,j) on the k-th channel. In this every negative value from the filtered images is replaced with zero.

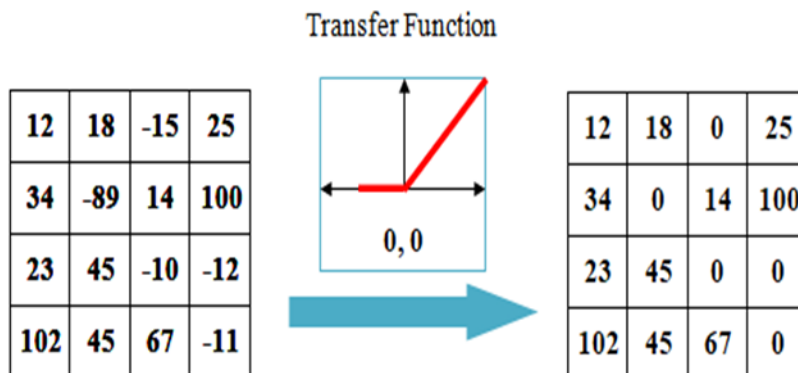


Figure 4. Relu Activation Function

### 3.4. Fully Connected Layer

The fully connected layer connects a set of neurons to each of the neurons of the previous layer. The flatten layer simply vectorizes and connects all of the neurons from the outputs of the previous layer to all of the neurons in the fully connected layer. All of the convolutional layer and the first fully connected layer use the rectifier linear activation function (ReLU). Several software packages are available to provide a framework for implementing neural networks. The work presented here uses Keras, which is a Python library that provides easy-to-use abstractions to powerful learning libraries such as Theano and TensorFlow (used here). Convolutional neural networks retain spatial information through filter kernels. In this work we exploit this unique capability of CNN to train a model to classify images.

## 4. Experimental Result and Analysis

In this section, we present and discuss the results of the proposed gender recognition system. We tested the system using a well-known public domain fingerprint database NIST DB4. First, we give an overview of these databases and the experimental setup used for each database. For evaluating our proposed approach, we have used the NIST DB4 dataset. This is a large fingerprint dataset used for gender classification, which contains 4000 images of size 512\*512, where 3200 are training images, and 800 are testing images. Some of the sample fingerprint images from the NIST dataset for different features such as Arch (A), Right loop (RL), Left loop (LL), Whorl (W), Tented arch (T) are shown in figure 5. Experiments are conducted on 2 classes such as male and female from the NIST DB4 dataset using a CNN model. The CNN model was trained and tested with 4000 images using tensor

flow in core i7 CPU 2.6 GHz, 1-TB hard disk, and 8-GB RAM. Sample training male and female fingerprint images are shown in figure 6.

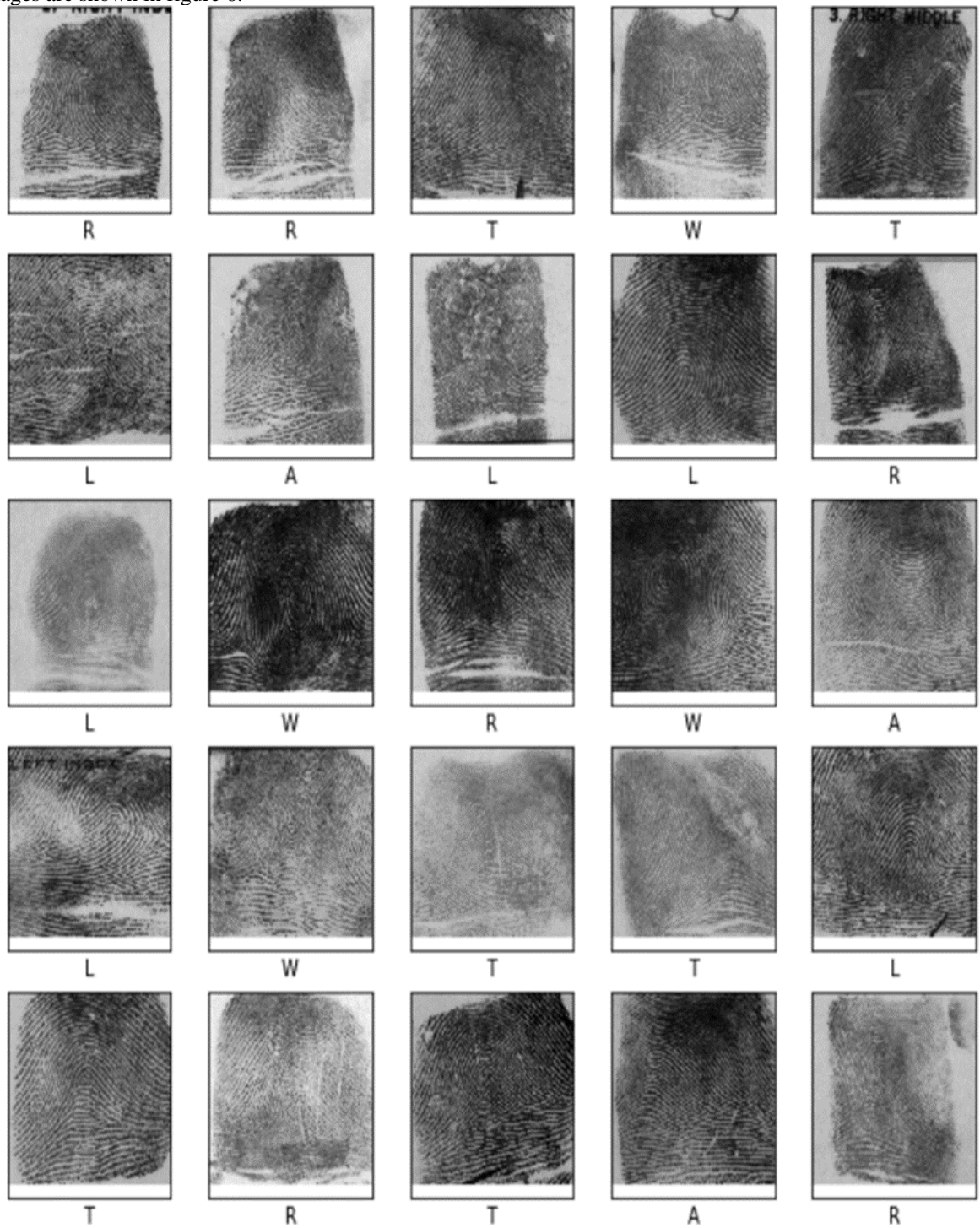


Figure 5. Fingerprint classes

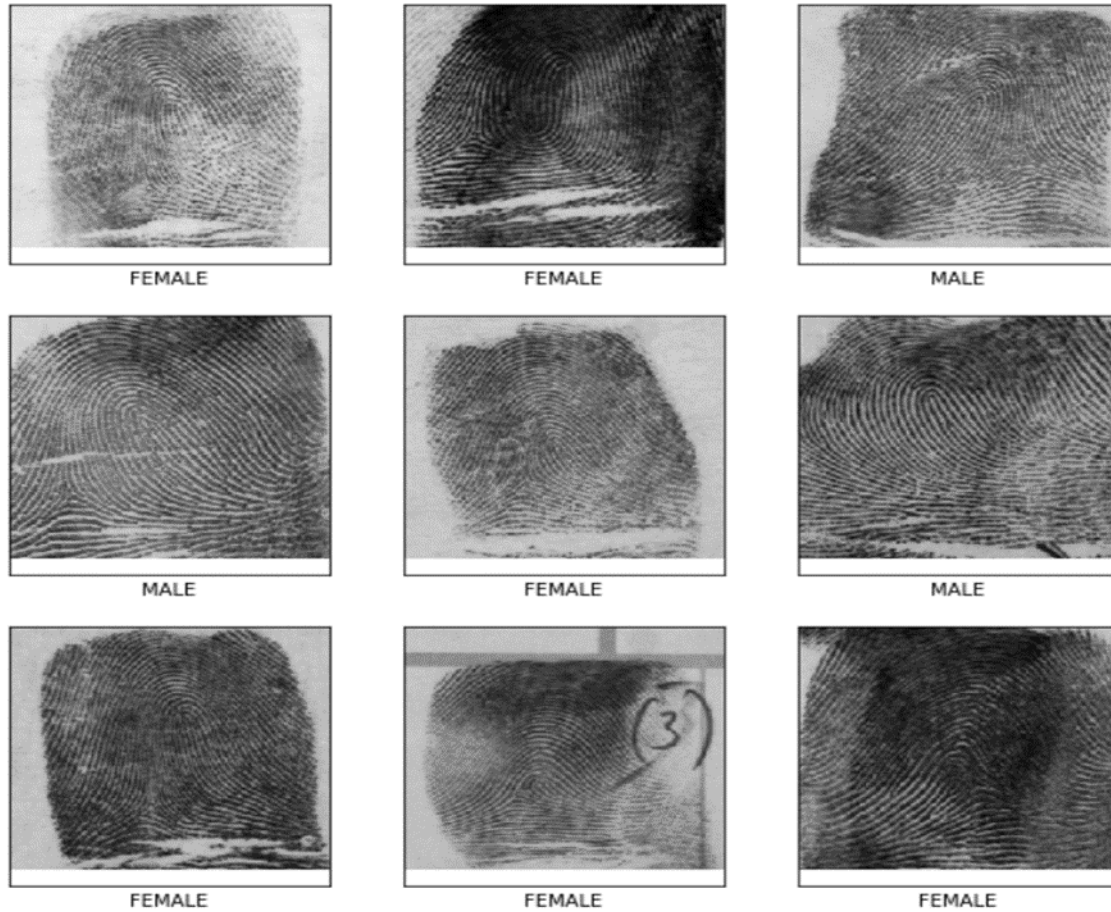


Figure 6. Sample input fingerprint images of male and female

Confusion matrix in figure 9 is used for summarizing the performance of our classification algorithm where the number of correct and incorrect predictions are summarized.

Table1. Confusion Matrix

Class Name	Male	Female
Male	99	1
Female	1	99

By using the four combinations of predicted and actual values such as TP, FP, TN, FN we have evaluated the performance of proposed framework. TP stands for true positive, which represents system has recognized positive as positive, TN means true negative which means system identifies negative as negative, FP is false positive which predicts negative as positive and FN is false negative which predicts positive as negative. Accuracy is defined as the ratio of the number of genders correctly classified to the total number of genders as given in equation 1. To illustrate the results more extensively we adopt Precision, Recall and F-measure which are defined by equations 2,3,4 respectively. F-measure is used as an evaluation metric for measuring regression performance of our proposed approach. The large value of F-measure indicates higher classification rate.

$$\text{Accuracy} = \frac{\text{Total no.of correct prediction}}{\text{No.of input samples}} \tag{1}$$

$$\text{PRE}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i} \tag{2}$$

$$\text{REC}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FN}_i} \tag{3}$$

$$F_1^i = \frac{\text{PRE}_i \times \text{REC}_i}{\text{PRE}_i + \text{REC}_i} \tag{4}$$

In this work we have fine-tuned the hyperparameters of activation functions namely ReLu and Tanh. Figure 7 shows one predicted output of the proposed model. Accuracy and loss curve of the proposed model is given in figure 8.

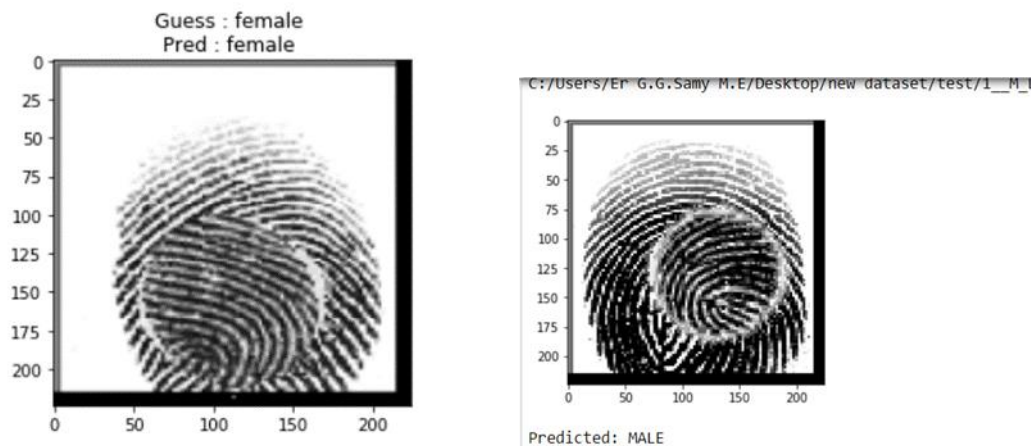


Figure 7. Classified Output

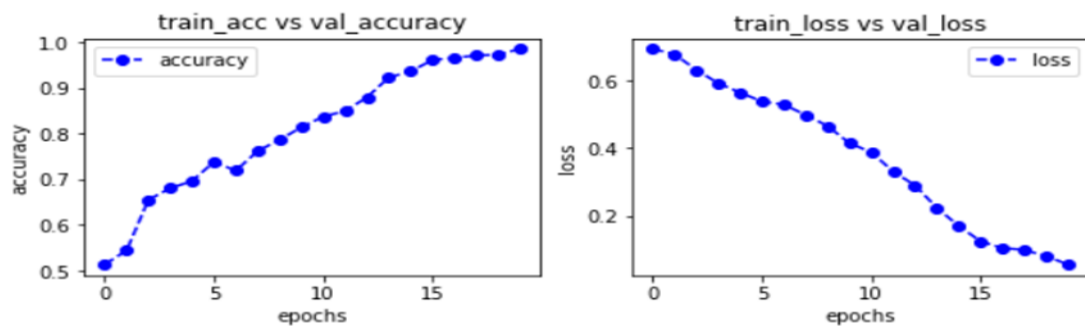


Figure 8. Accuracy and Loss graph for the proposed model

Table 2 displays the values of performance metrics of the proposed approach and Figure 10 is the corresponding chart. Performance metrics table shows that the proposed approach with Relu activation function efficiently classified the image with an accuracy of 99% and an accuracy of 74.5% for Tanh by training the network model for 20 epochs.

Table 2. Performance Metrics of the proposed approach

Activation function	Epochs	Accuracy	Precision	Recall	F1-score
ReLu	10	88.5%	87.7%	88.2%	88%
	20	99%	99%	99%	99%
Tanh	10	85.2%	85.1%	84.8%	85%
	20	87.6%	87.3%	87.2%	87%

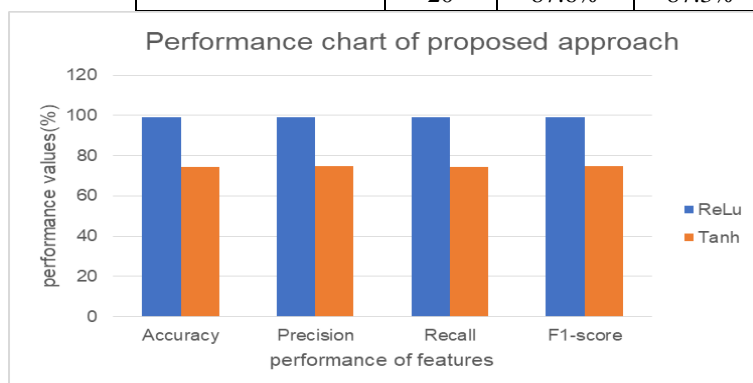


Figure 9. Performance chart of proposed approach

## 5. Conclusion

In this paper, we have proposed a gender classification model which is a easy task of humans but not to machines. CNN which is one of the widely used model to classify images is employed to classify gender based on fingerprint images. We have trained the convolutional model with images from NIST DB4 using the activation function ReLu and Tanh for epochs ranging from 10 to 20. We got the optimal performance of 99% accuracy for Relu activation function at 20th epoch. This model can be used to reduce search space in other applications such as identification & authentication. Our upcoming work direction is to analyse the performance by using other deep learning classifiers.

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