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Fingerprint analysis for gender classification using Deep Convolutional Neural Network

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Abstract: Fingerprints are the most widely used unique proofs for recognizing the individuals. In this work, we used human fingerprint images as a confirmation to regulate the classification of person. Fingerprints are broadly used for recognizing individual but gender prediction is a developing field. In this work we used a Deep Convolutional Neural Network (DCNN) to classify the gender classification. This experiment is tested with the internal database of NIST dataset contains 1000 images of size 154×192, where 900 are training image, and 100 are testing image. The Dataset can be classified into two classes: they are (male and female). Experimental results attained 80% in Deep CNN. Thus the deep CNN shows better performance for gender classification using fingerprint images.

Index Terms - **Fingerprints, Deep Convolutional Neural Networks, Biometrics and Gender classification**

I. INTRODUCTION

Fingerprint is a biometric which is an epidermis representation of a finger. Epidermis includes ridge and valley patterns. Like all other biometric features, fingerprint ridges are formed as a combination of genetic and environmental factors and are called as dermatoglyphics. The statistics of dermatoglyphics differ between genders, ethical groups and age categories. Fingerprint is widely used in forensic anthropology because of its unique nature and do not change throughout the life of an individual.

Fingerprint based age identification will be useful for those people working in forensic system to focus only on the predicted age group, which can improve the search speed and efficiency of the retrieval system by minimizing the subsequent searching space. Age information is important to provide investigative leads for finding unknown person. Existing methods for age classification in crime investigation depend on the availability of teeth, bones or other body parts.

To determine person peers some natural ways are created using soft biometrics instances. The major part of the advantages of biometrics and approve of its own assets is inherited by soft biometric traits.

Identifying the gender classification of the crime scene is an important issue in minimizing the subsects of forensic science. Exiting method into gender recognizing have limited use in crime scene investigation such as making a age and gender recognized. Gender classification from fingerprint is new and important research topic for important crime scene. Recognizing gender from the fingerprints of people is a developing area.

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 for 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.

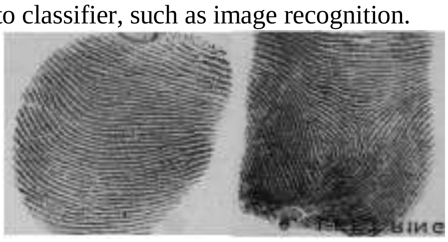

Fig. 1 fingerprint images as male and female

II. RELATED WORK

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. Emanuela marasgo [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 determinating 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 fingerprints 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 RBF_sigma 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.

III. Proposed Work

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

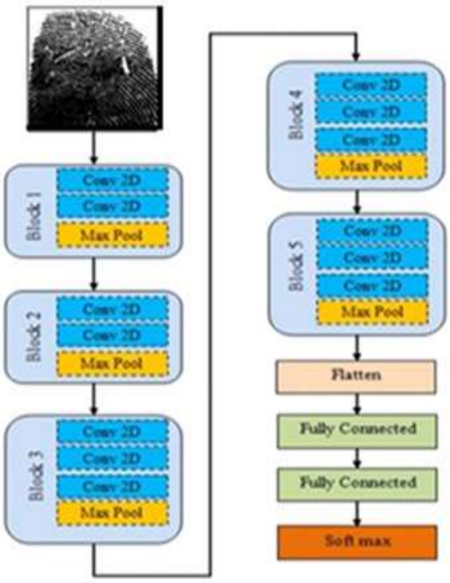

Fig 2: Deep CNN architecture

This section describes the Deep CNN model for classification of gender prediction using deep CNNs. This model consists of 13 convolutional layers with 3×3 filter size, five subsampling/max pooling layer with a size of 2×2, and two fully connected layers with activation function and Soft-Max function. The convolutional layer's extract features from the input images. The 13 convolutional layers are described in five blocks. The first two block contain two convolutional layers in each block. In another three blocks consist of three convolutional layers in each block. The first block convolutional layer extracts the low-level features such as lines and edges. Higher level layer extracts the high-level features.

3.1Pooling layer

Every convolutional layer filter has a kernel size of 3×3. The filter size of the convolutional gradually increased from 64 to 512. Thus, figure2 has shown in Deep CNN model Sub-sampling. 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 be computational time also. There are three types of pooling layers: max pooling, minimum pooling, and average pooling. 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.

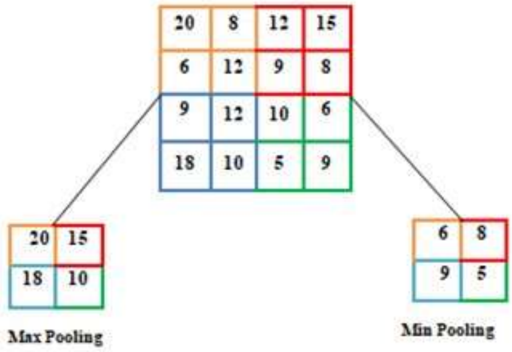

Fig 3: Max pooling and Min pooling process

3.2The Fully connected layer

The deep CNN model ends with two fully connected layer and Soft-Max function. The fully connected layer connects a set of neurons to each of the neurons of the previous layer. The flatten layer simply vectorises 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).

3.3 Activation Function

The activation function improves the deep CNN performance. There are three familiar activation function such as Sigmoid, Tanh and Relu. The performance of the standard activation function Relu has been activation function in this paper. Its role is to remove every negative values from the filtered images and replace it with zeros which is depicted in figure 4. The relu activation function is defined as: The ReLU activation function is defined as:

$$b_{i,j,k} = \max(a_{i,j,k}, 0) \qquad (1)$$

where, ai,j,k is the input of the activation function at location (i, j) on the k-th channel. 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 Deep CNN to train a model to classify images.

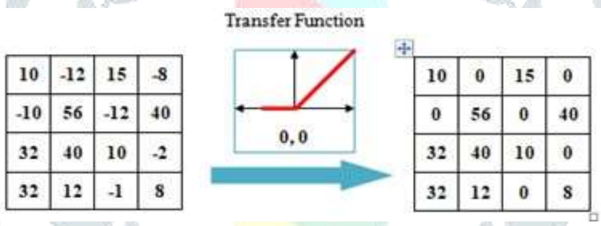

Fig 4: Activation function

IV. Experimental Result

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 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 image, and 800 are testing image. Some of the sample fingerprint images from NIST dataset.

Experiments are conducted on 2 classes such as male and female from the NIST DB4 dataset using Deep CNN model. The Deep 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.

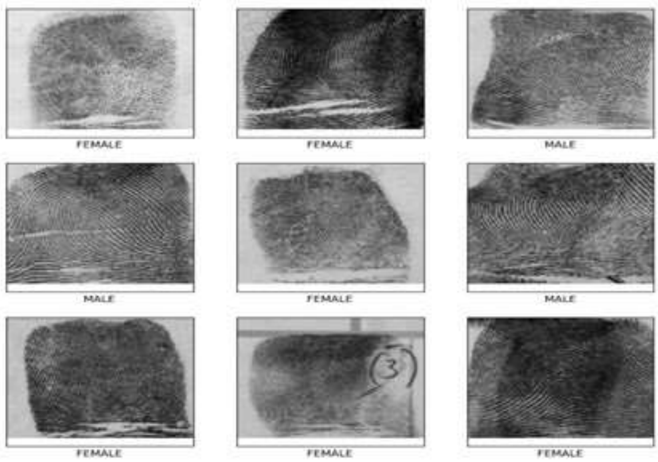

Fig 5: Fingerprint images as male and female

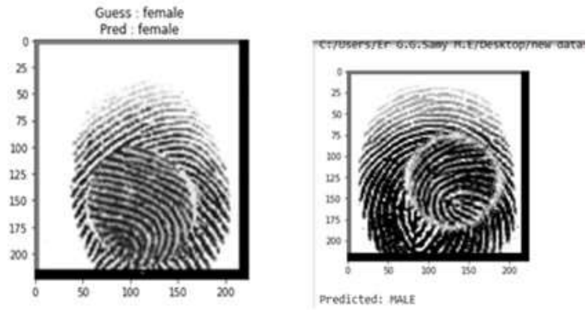

Fig 6: Classified outputs

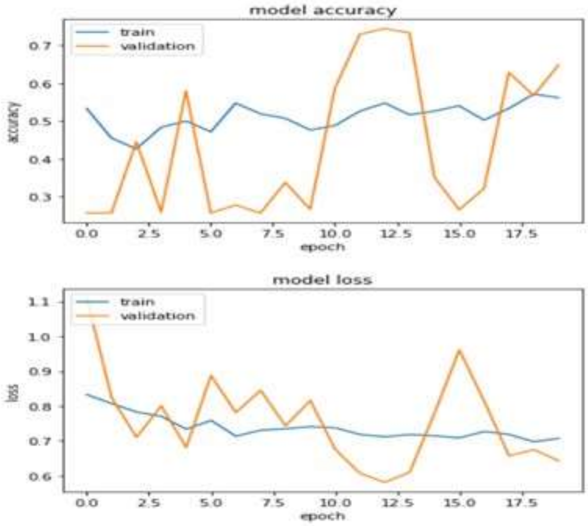

Fig 7: Accuracy and Loss graph for the proposed model

Confusion metrics- Confusion matrix in figure7 is used for summarizing the performance of our classification algorithm where the number of correct and incorrect predictions are summarized.

Table 1 Confusion Matrix

Class Name	Male	Female
Male	85	15
Female	10	90

By using the four combinations of predicted and actual values such as TP, FP, TN and 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 gender correctly classified to the total number of gender as given in equation 1. To illustrate the results more extensively we adopt Precision, Recall and F-measure which are defined by equations2,3,4 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.

$$Accuracy = \frac{Total\ no.of\ correct\ prediction}{No.of\ input\ samples} \quad (2)$$

$$PRE_i = \frac{TP_i}{TP_i + FP_i} \quad (3)$$

$$REC_i = \frac{TP_i}{TP_i + FN_i} \quad (4)$$

$$F_1^i = \frac{PRE_i \times REC_i}{PRE_i + REC_i} \quad (5)$$

In this work we have fine-tuned the hyper-parameters of activation functions namely ReLu. Table 1 displays the values of performance metrics of the proposed approach and Figure 9 is the corresponding chart. Performance metrics table shows that the proposed approach with Relu activation function efficiently classified the image with an accuracy of 80% by training the Deep Convolutional neural network model for 20 epochs.

Table 2 Performance metrics of the proposed approach

Activation function	Epochs	Acc.	Precision	Recall	F1-score
ReLu	20	81%	80%	76%	82%

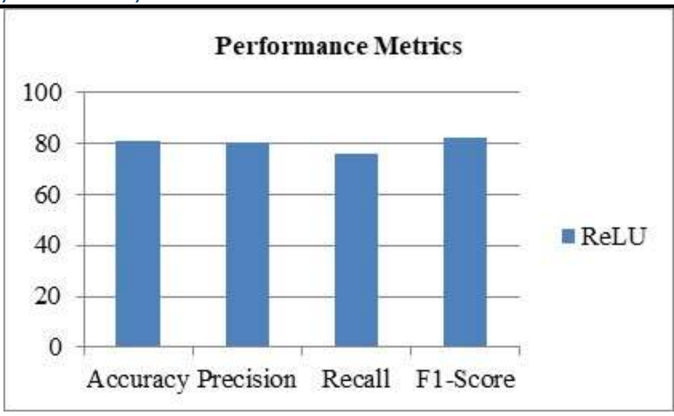

Fig 8: performance chart of proposed approach

V. Conclusion

In this paper, we have proposed a gender classification model which is an easy task of humans but not to machines. Deep Convolutional Neural Network (DCNN) which is one of the widely used model to classify images is employed to classify gender based on fingerprint images. We have trained the Deep convolutional model with images from NIST DB4 using the activation function ReLu for epochs ranging from 20. We got the optimal performance of 80% 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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