ISSN No:-2456-2165

Deep Gender Identification Model with Biometric Fingerprint Data

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Abstract:- People may be easily distinguished from one another thanks to their distinctive and special traits, which also serve as a means of identification. One of the most important pieces of identification information is gender. If we can confidently determine a person's gender, it will reduce the number of inquiries and shorten the search period while increasing the likelihood that someone will be recognized. In this work, we apply deep convolution Neural Network to classify fingerprints by means of gender. The proposed model achieves an validation accuracy of 96.46% for the classification of gender. Publicly available Sokoto Coventry Fingerprint Dataset (SOCOFing) is applied as a benchmark for the outcome of the classification accuracy of the proposed network.

Keywords:- *Biometric, Fingerprint, Deep Learning, CNN,Gender Identification,)*

I. INTRODUCTION

Biometric data includes a person's voice, signature, handwriting, iris, fingerprint, face, and other measurable, distinguishing physical characteristics. Biometric data is gaining popularity as a security tool since it is unique to each individual and offers a high level of security. One distinguishing feature of the fingerprint is that each individual's form is unique and does not change over the course of a lifetime [1] [2]. A fingerprint may therefore be used to precisely identify and confirm a person, and it has recently become used for mobile devices like smart phones as a rapid identification method [3]. The interpretation of fingerprints is dependent on the Locard's Principle of Exchange. The discharges found in fingerprints include traces of different chemicals and their metabolites, which can be discovered and used for forensic analysis. They can be found at the crime scene, making it easy to confirm the presence of a suspect, victim, or anybody else. These days, fingerprints are routinely used in workplaces and educational establishments to verify a person's existence [4] [5]. Although the human vision system is self-sufficient and quite adaptive in roughly recognizing someone's age and gender, it is still difficult or impossible for the machine to tell whether a male or female fingerprint belongs on a person. As a result, gender identification [6] [7] based on any biometrics bisects the search space.

Only a small number of academics have studied fingerprints for gender categorization and unearthed the best outcomes. In this proposed work, we are trying to develop a deep convolution network which can accomplished classification of gender [8] [9] from fingerprint with competing with acceptable outcomes. The manuscript is organized as follows: Section I, following the introduction, related work in section II and proposed methodology in Section III. The outcome of the proposed method is discussed in Section IV and remaining conclusion and future scope in Section V and Section IV respectively.

II. RELATED WORK

In the recent past, there has been a lot of study into fingerprint identification and classification. But relatively few studies have looked into the issue of gender categorization and identification using fingerprints. Ahmed Badawi et. al. [6] devised a Gender categorization from fingerprints, which is a crucial step in forensic anthropology. An analysis was done on a collection of 10 fingerprint pictures representing 2200 people of various ages and genders (1100 men and 1100 females). Ridge count, ridge thickness to valley thickness ratio.

(RTVTR), white lines count, ridge count asymmetries, and pattern type concordance were among the features collected. To classify data based on the most prevalent characteristics, Fuzzy - C Means (FCM), Linear Discriminant Analysis (LDA), and Neural Network (NN) were employed. They used FCM, LDA, and NN to get outcomes of 80.39%, 85.5%, and 88.5%, respectively. Ashish Mishra et. al. [10] successfully reduce search time by managing the searching stage for both right hand and left-hand thumb datasets using the classifiers SVM and Naive Bayes. Prabha et. al. [11] proposed a research technique of gender categorization using fingerprints which is based on characteristics that were retrieved using Discrete Wavelet Transform. S.S. Gornale et. al. [7] put into practice a cutting-edge method for gender detection using fingerprint pictures. KNN and LBP classifiers are employed. The gender detection percentage for a collection of male and female fingerprint pictures using this method is 95.88%. A method developed by S. Falohun et. al. [12] uses fingerprint analysis to determine a person's age and gender. Machine is trained using integrated DWT & PCA characteristics (for age classification). Ridge / Valley count with Back Propagation Neural Network is used to classify the gender using Ridge Thickness Valley Thickness Ratio characteristics. Mangesh Shinde et. al. [13] used SVD and DWT to identify a person's gender by utilizing fingerprint. In the research, the fingerprint image is examined up to six levels of DWT and SVD separately, followed by the combined result vector of DWT and SVD. Overall accuracy rates for both male and female participants in the trial were 78.65%. Rekha et. al. [14] uses Gabor filter and Support Vector Machine for gender classification from fingerprint. The Adaptive Nero-Fuzzy Inference System (ANFIS) approach is used by Suman Sahu et. al. [15] to identify fingerprint gender. Frequency Domain Analysis (Frequency-based properties including vertical, horizontal, amplitude, and diagonal) and RVA must be extracted in order to group fingerprint images as female or male. Terh¨orst et. al. [16] demonstrated that a single minutia's gender choice accuracy is linearly correlated with its dependability, and that adding this information in the fusion process improves performance. A feature vector made up of the ridge thickness to valley thickness ratio (RTVTR) and the ridge density values was used by Sarath et. al. [17] to represent each fingerprint in the database. They achieve a reliable classifying function for male and female feature vector patterns using a support vector machine trained on a batch of 150 male and 125 female fingerprints. Merkel et. al. [18] uses the capturing devices (CWL and CLSM), to capture fingerprint images, that covers ten dissimilar datasets with entire 2,618 time-series. Correlation coefficients and age estimate based on machine learning are the supplied baseline findings for age estimation on all 10 sets. Shivanand Gornale et. al. [19] employed Gabor and DWT-based characteristics to classify fingerprints into male and female categories. The fingerprint pictures of 74 individuals, representing a range of ages and genders, were acquired for the system's training.

III. PROPOSED METHOD

A. DataSet:

Training and testing of the proposed method, was carried out using publicly available dataset named Sokoto Coventry Fingerprint Dataset (SOCOFing) [20]. The dataset contains 6000 real fingerprint images which again treated with obliteration, central rotation, and z-cut with different degree to form altered easy, altered medium and altered hard fingerprints images. The size and other details of the dataset is shown in the Fig 1.

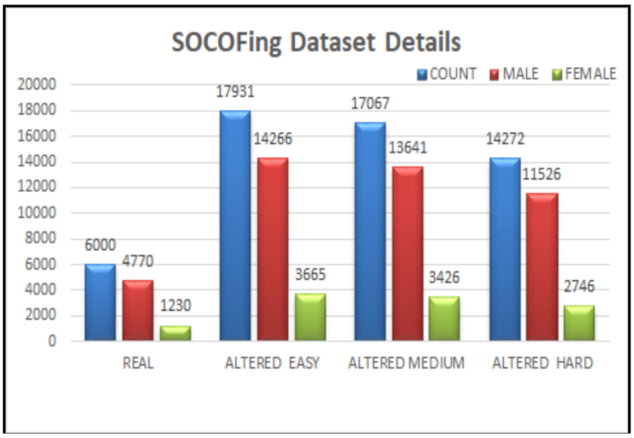

Fig. 1. Details of Dataset SOKOFIG

B. Workflow:

The fingerprint images from SOCOFing dataset is first preprocessed and resized to 96x96 for the input of the proposed deep learning model. The detail work flow of the proposed method is shown in the Fig 2.

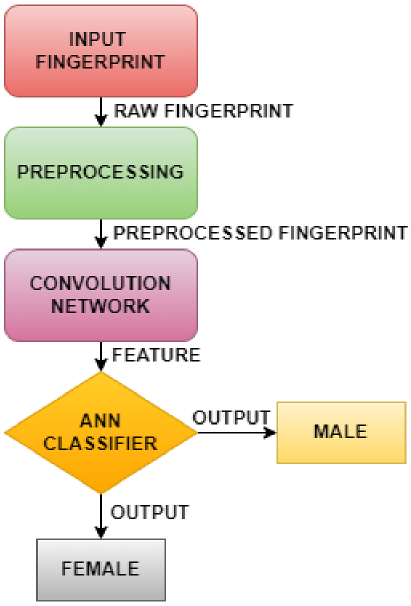

Fig. 2. Proposed methods' Workflow

C. Preprocessing:

Prior to training and testing, the 96x103 pictures in the dataset are downsized to 96x96 and given a grey label value of 0-1. Three sets have been created from the dataset. A total of 14781 photos were utilized for testing, 10347 images for validation, and 24142 images for training.

D. Network Architecture:

A four-convolution layer is used to extract features from the input fingerprint, which is then followed by batch normalization and maxpooling. The final extracted feature is obtained by doing a global maxpooling operation following the convolution procedure. The extracted feature is passed to a artificial neural network containing 128 hidden node which classify the feature in to required output of male / female. Fig 3 displays the network architecture of the proposed method.

E. Network Hyperparameter:

Activation function used in convolution layer is rectified linear unit and he uniform is used as initial network weight assignment. Softmax activation function is used in the fully connected dense layer of the artificial neural network classifier. For optimization of the performance of the network Adam optimizer is used in the proposed network. Finally categorical cross entropy is used as the loss function of the network, which is minimized by the proposed network. Fig 4 depicts the specifics of the proposed network.

F. Network Training:

With a batch size of 64 the network was trained for 100 epochs to achieve the desired accuracy of the classification of gender from fingerprint. The network takes approximated 12 hours for training the part of whole dataset used for training.

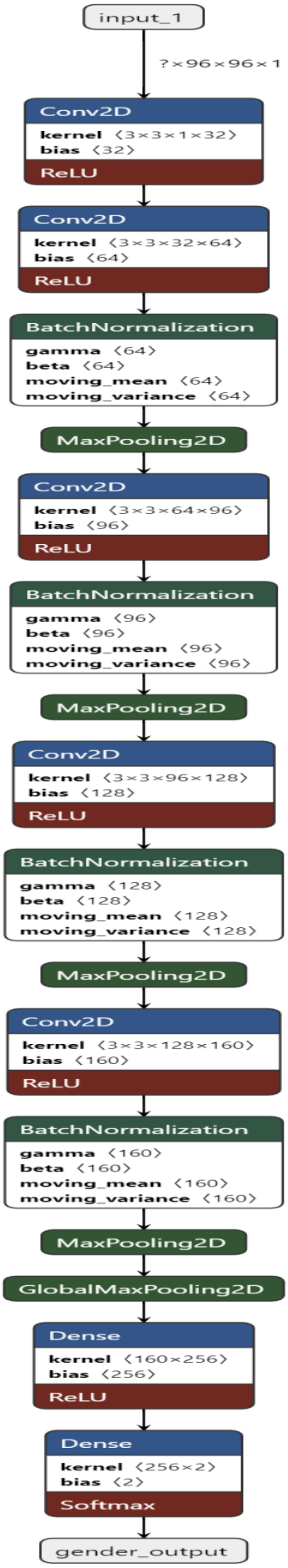

Fig. 3. Proposed Network Architecture

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 96, 96, 1)]       0
 conv2d (Conv2D)             (None, 94, 94, 32)        320
 conv2d_1 (Conv2D)           (None, 92, 92, 64)        18496
 batch_normalization         (None, 92, 92, 64)        256
 (BatchNormalization)
 max_pooling2d              (None, 46, 46, 64)        0
 (MaxPooling2D)
 conv2d_2 (Conv2D)           (None, 44, 44, 96)        55392
 batch_normalization_1       (None, 44, 44, 96)        384
 (BatchNormalization)
 max_pooling2d_1            (None, 22, 22, 96)        0
 (MaxPooling2D)
 conv2d_3 (Conv2D)           (None, 20, 20, 128)       110720
 batch_normalization_2       (None, 20, 20, 128)       512
 (BatchNormalization)
 max_pooling2d_2            (None, 10, 10, 128)       0
 (MaxPooling2D)
 global_max_pooling2d        (None, 128)               0
 (GlobalMaxPooling2D)
 dense (Dense)               (None, 128)               16512
 gender_output (Dense)       (None, 2)                 258
=================================================================
Total params: 202,850
Trainable params: 202,274
Non-trainable params: 576
_________________________________________________________________
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Fig. 4. Proposed Network Parameter Details

IV. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

We conducted extensive experiments using deep convolution networks to demonstrate the usefulness of our suggested technique. Table I shows the accuracy, loss value of training and validation for gender identification. In Table II the proposed methodology has been compared with other methodology from the related current work in view of classification performance for gender identification for one batch. The classification report of the proposed network is conveyed in the Table III. Fig 5, Fig 6, Fig 7 and Fig 8 displays the training and validation accuracy, training and validation loss, Precession and recall with receiver operating characteristic curve of the proposed model during training and testing.

Table 1 Training & Validation Accuracy And Loss For Gender Classification

Gender Identification	Accuracy	Loss Value
Training	99.86%	0.0034
Validation	99.33%	0.0266

ISSN No:-2456-2165

Table 2 Comparison of Proposed Method with Current Work.

Sl No.	Title	Method Used	Accuracy
1	Badawi et. al.[6]	FCM, LDA, NN	80.39%, 85.5%, 88.5%
2	Sheetlani et. al.[11]	BPNN	96.6%
3	S.S. Gornale et. al.[7]	LDA & QDA	95.8%
4	A. S. Falohun et. al.[12]	ANN	80%
5	S.S. Gornale et. al.[19]	KNN, LBP	95.8%
6	Mangesh et. al.[13]	SDV, DWT	78.6%
7	**Proposed Method**	**CNN**	**99.33%**

TABLE III
CLASSIFICATION REPORT FOR GENDER

	Precision	Recall	F1-Score	Support
Male	0.99	0.99	0.99	111
Female	0.94	0.94	0.94	17
Accuracy			0.98	128
Macro Avg	0.97	0.97	0.97	128
Weighted Avg	0.98	0.98	0.98	128

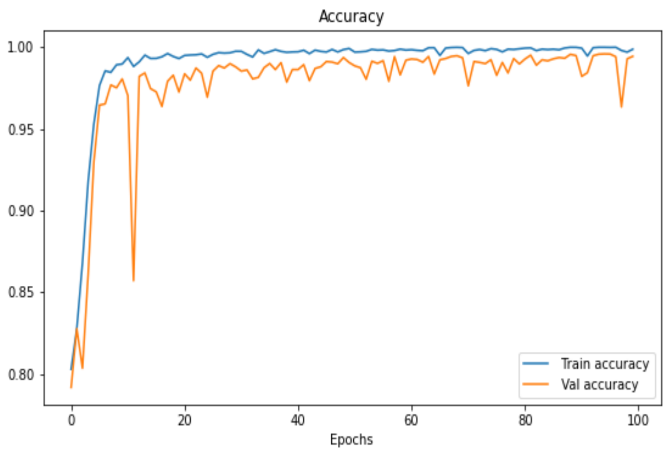

Fig. 5. Training and Validation Accuracy

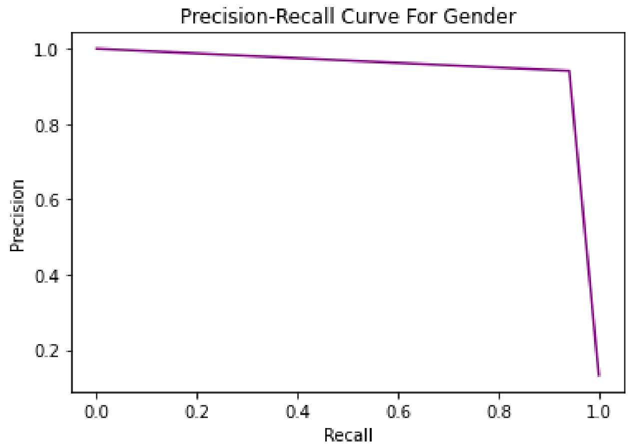

Fig. 7. Precession & Recall of the Network

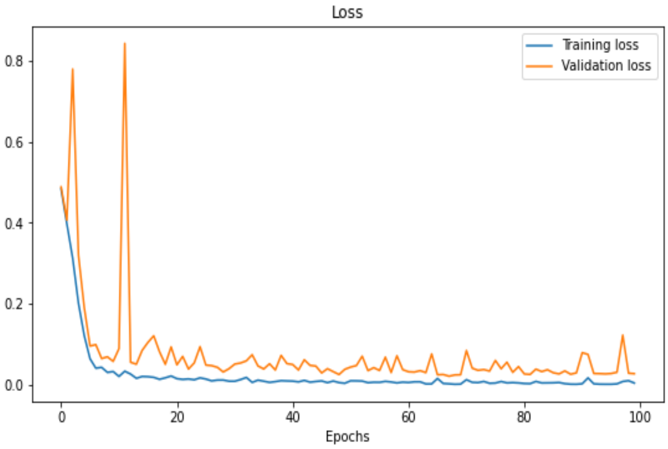

Fig. 6. Training and Validation Loss

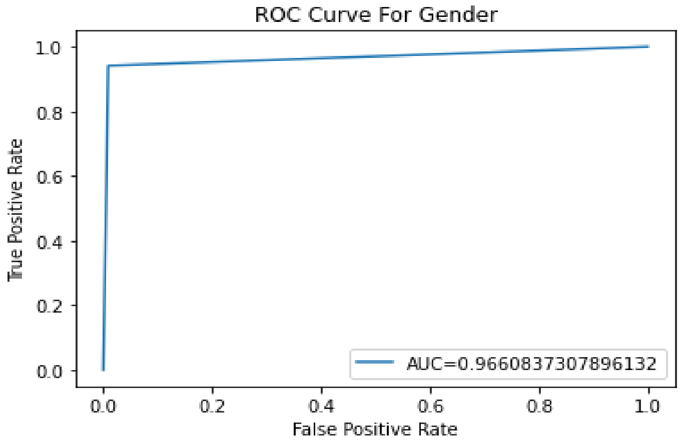

Fig. 8. ROC Curve of the Network

Sample output of the proposed technique is displayed in Fig 9.

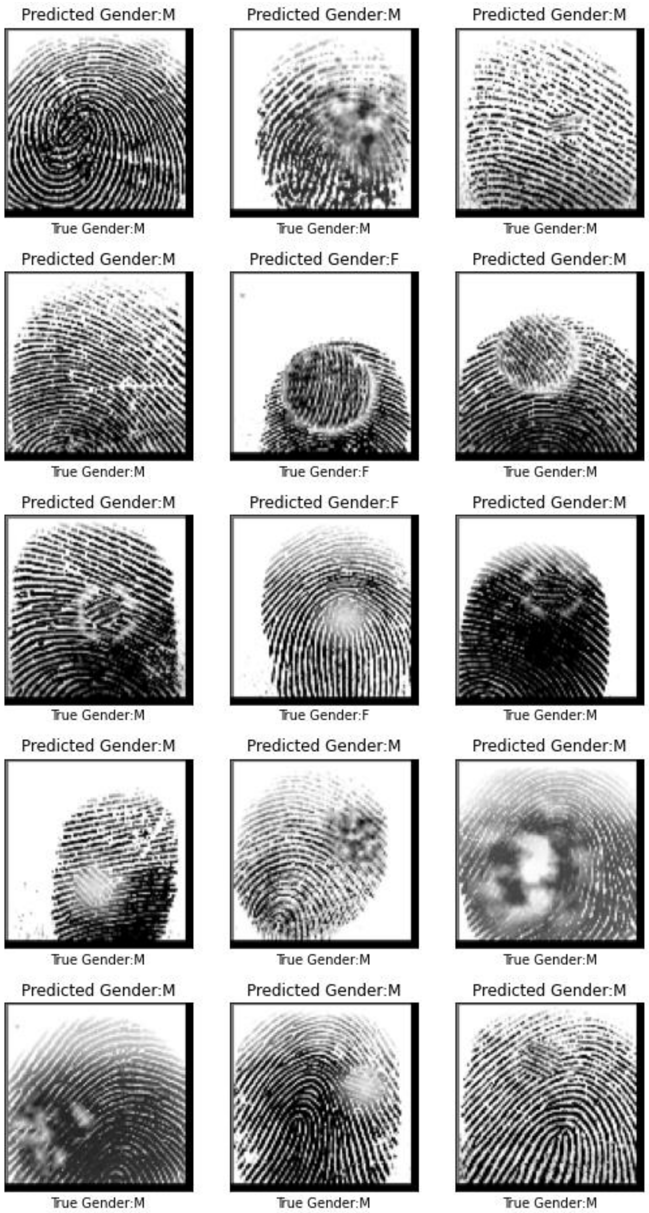

Fig. 9. Sample Output of the Proposed Technique

V. CONCLUSION

Due to the huge potential of fingerprints as an effective means of identification, an attempt has been made in the current study to analyze the link between fingerprints and gender of an individual. The results of gender classification using these dominant traits suggested that this technique might be a good contender for use in forensic anthropology to narrow the list of prospective suspects and offer a likely probability value for a suspect's gender.

VI. FUTURE SCOPE

We'll also aim to improve the gender classification by fusing the fingerprint features obtained by the convolution layers with the minuscule points utilized in the fully connected layer. We'll be contrasting our novel approach with other classifiers in future study. We will look at whether additional factors, such as fingerprint thickness or valley thickness, may improve the capability of deep CNN models for classification.

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