Detailed Identification of Fingerprints using Convolutional Neural Networks

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***Abstract*—Fingerprints, as one of the most widely used biometric modalities, can be used to identify and distinguish between genders. Gender classification is very important in reducing the time when investigating criminal offenders and gender impersonation. In this work, we use deep Convolutional Neural Networks (CNNs) to not only classify fingerprints by gender, but also identify individual hands and fingers. Transfer learning is employed to speed up the training of the CNN. The CNN achieves an accuracy of 75.2%, 93.5%, and 76.72% for the classification of gender, hand, and fingers, respectively. These results obtained using our publicly available Sokoto Coventry Fingerprint Dataset (SOCOFing) serve as benchmark classification results on this dataset.**

Keywords— Convolutional Neural Networks, Fingerprints, Gender Classification, Transfer Learning

I. Introduction

For over a century now, fingerprints have been extensively used for person identification. Fingerprints are the unique patterns that are persistent and cannot be easily change [1]. Fingerprints are composed of many ridges and furrows, and they are a unique marker of a person. No two identical fingerprints have ever been found. Features of the fingerprints statistically differ between genders and age categories [2]. Personal identification is essential in security and video surveillance applications. An individual can be recognized by various features, such as body, voice, stature, and shape. Gender is one of the most essential features that separates between people. Fingerprinting is considered the best technique for distinguishing between individuals and for tracking criminals [3]. And it has been proven by many researchers that fingerprints can be used for gender classification, which is helpful when short-listing suspects [4-7].

The uniqueness of the fingerprint features can reduce the gender identification difficulties and limit the amount of time it takes to identify a suspect. These unique features of fingerprints can be used in differentiating between individuals by their gender and, therefore, it makes faster the identification processes of unknown suspects. Furthermore, it can guide forensic investigators to the correct identity of a suspect when matching the suspect's fingerprints among the large number of possible matches in the fingerprint databases. It is extremely time consuming to identify and detect unknown fingerprints in a large volume of fingerprint databases during investigation. However, by knowing the gender, hands or fingers will grossly reduce the time it takes in identifying the culprit in a large volume fingerprint database. Usually, at the initial stage of forensic investigation, if a suspect can be deduced to be either a male or female, the forensic investigators will limit the scope of the investigation and hence speed up the forensic investigation.

The use of biometric fingerprints to unlock mobile phones is on the high increase due the added security to mobile phones, yet they can be hacked [8] with spoofed fingers. This is an indication that a mobile phone can be unlocked irrespective of gender. Building a model that can identify the gender is really necessary to boost the security of the mobile phones technology.

At the border control, such systems will also help in detecting and differentiating between genders. This is because some individuals may impersonate gender with the intention of evading identification. Gender crime impersonation is a challenge that needs to be solved not only through physical investigation but also using biometric fingerprints. Crime impersonation is possible as indicated in [9], where credentials like international passports, certificates and driver licenses can be forged by deceitful criminals with technical skills despite the security features added in them. However, biometric features like fingerprints will help reduce the threat of counterfeiting [10].

In this paper, we propose using CNNs for gender, hand and finger classification and report benchmark results on our publicly available SOCOFing dataset. The paper is organised as follows: Section II describes various works in relation to biometric fingerprints and gender classification; The dataset used for the experimentation in this paper is discussed in section III; The methods and the experimental setup is described in section IV; Section V highlights the results, analysis and discussion of the results; Finally, the conclusions and future works are described in section VI.

II. Related Work

Different studies on gender determination carried out so far are based on the three-dimensional domain scrutiny of ridges. Previous studies have used ridge associated parameters for gender identification, which include: fingerprint ridge tally, thickness, thickness to valley proportion, width, finger impression designs and design styles. Some experimental results presented in many studies show that females reveal a greater ridge thickness due to better and clearer epidermal ridge details compared to males [11]. Nithin et al. [5] present a study which aimed at determining the gender based on finger ridge count within a distinct region of Southern India. A sample of 550 rolled-finger fingerprints was taken, in which

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275 were from men and 275 from women, all of them in the age limits of 18 - 65 years. The outcomes of the research indicate that female have an ominously greater ridge count than their male counterpart. The application of Bayes' theory in this study suggests that a fingerprint possessing ridge density less than 13 ridges per 25 mm^2 is most likely to be of male origin. Likewise, a fingerprint having a ridge count greater than 14 ridges per 25 mm^2 is most likely to be of female origin.

Authors in [12] present another study on different techniques for gender identification using fingerprints. The study proposed different ridge related approaches used for gender identification, like unique finger impression edge check, thickness, width and unique finger impression patterns. The study identifies the frequency domain approaches as the most efficient method, because of its flexibility and less computation time required when compared with the spatial domain approaches.

The authors of [13] conducted a research on fingerprint gender classification using wavelet transforms and Singular Value Decomposition (SVD) methods. A sample of 3570 fingerprints was taken, in which 1980 fingerprints all from male and 1590 fingerprints all from female. They proposed a new method for classifying gender based on fingerprint images, by using discrete wavelet transforms and Singular Value Decomposition. The techniques considered the spatial features of the singular value decomposition, which includes the internal structure of the fingerprint images and the frequency features of the wavelet domain, and which improved performance in gender classification. The result indicates that the female fingerprints show significantly higher classification rates than those of males. Gender classification for subjects male tested attained 91.67% accuracy rate, and 84.69% for females, respectively.

Classification of gender from fingerprints was also proposed by [7], which recognize the gender of a criminal and help in decreasing the suspect search time. Their research analysed a dataset of 10 fingerprint images for 2200 people of different gender and age using feature extraction techniques. Neural networks, Fuzzy C-means and linear discriminant analysis were used, and classification results of 88.5%, 80.39%, and 86.5% were obtained, respectively. Furthermore, an implementation of a novel method to classify gender was presented by [18] using two combined methods of wavelet transformation to extract fingerprint features and pass the output to back-propagation neural network algorithms for the final gender classification. The experimentation was performed using a fingerprint database of 275 male and 275 female fingerprints, and obtained a classification accuracy of 91.45%.

CNN based models have proven to be robust in image classification tasks. Previous work [14] has demonstrated that CNNs can be used for fingerprint classification and produce remarkable results. Therefore, detailed classification of fingerprint using CNNs will help provide a more effective method for gender, hand and finger classifications. Previous methods for fingerprint gender classification used hard coded features of the fingerprints for gender classification. With a CNN, the model learns the features to distinguish between genders, which makes it better, as it takes into consideration every bit of the fingerprint image information. This fingerprint image information is critical for distinguishing between fingerprint images, as the patterns of the fingerprint images retain the required information for the classification.

Transfer learning is also considered in this work for faster learning of a CNN classifier [15], [16]. More precisely, this work employs a ResNet model originally trained on ImageNet, as the source domain, and adapts it to the domain of fingerprint classification.

III. Dataset

Out of the total 6000 images in our publicly available Sokoto Coventry Fingerprint Dataset, 4770 belong to male subjects and 1230 to female subjects [17]. In order to provide a fair comparison, we only utilize for gender identification a subset of 1230 images from male subjects and all of the images available for females. This also ensures that the model does not favor a particular class and reduces the risk of overfitting. We refer to this subset as the SOCOFing-Gender, for simplicity. Similarly, for hand identification, there are 3000 images from left hands and 3000 from right hands. All of these images are used for hand identification; and this subset is referred to as SOCOFing-Hands. Lastly, SOCOFing also contains an even number of images for each individual finger: 600 images for each of the 10 fingers. These images are used for finger identification and, since it includes all images from the corpus, it is simply referred to as SOCOFing. All three resulting datasets are divided into 70% for training and 30% for testing.

Fig. 1. Top row is Left and Right hand fingerprints of a male subject, and bottom row is the Left and Right hand fingerprints of a female subject.

IV. METHODOLOGY AND EXPERIMENTATION

Convolutional neural networks have a unique ability to retain spatial information through filter kernels. Moreover, the salient features extracted by convolutional kernels are translation invariant. Given an input image I and a filter kernel K with $m \times n$ dimensions, their output can be summarized as:

$$\mathrm{C(i,j)} = (\mathrm{I} * \mathrm{K})(\mathrm{i,j}) = \sum_{\mathrm{m}}\sum_{\mathrm{n}} I(m,n)K(j-m, j-n)$$

These unique abilities of deep CNNs have made them standard models for image classification and other visual processing tasks. Nonetheless, training very deep CNNs remains a challenge due to problems such as lack of data, incorrect parameter initialization, or incorrect network topology, among others.

Transfer learning and domain adaptation (TLDA) can facilitate training by taking advantage of transferable features learned by a model and adapting the model from a source domain to a different domain. In this work, we employ TLDA as a base learning paradigm and employ ResNets originally trained on ImageNet for image classification [16]. ResNets are convolutional networks composed of residual blocks, which are blocks of layers with identity shortcut connections that skip two layers, reusing features learned in earlier layers and facilitating the flow of information. Identity shortcuts result in easier training, which in effect facilitates increased network depth. Moreover, because ResNets can be very deep, this eliminates the need for wider networks, which often have a significantly larger number of parameters and are more prone to overfitting.

Since ImageNet has over one million images spanning across one thousand classes, the resulting convolutional filters have the ability to identify a wide range of large and small salient features, therefore making them suitable for feature extraction in other domains, such as gender identification through fingerprint images.

For gender and hand classification, we employ two ResNet-34 models, i.e. with 34 parametrised layers, and fine-tune them on the training subsets of the SOCOFing-Gender and SOCOFing-Hands corpora. Both models are fine-tuned using mini-batches of size 128, momentum of 0.9, and a weight decay of 0.01 for 30 epochs. Similarly, we employ a ResNet-18 model and fine-tune it on the SOCOFing corpus for 50 epochs, using mini-batches of size 256 and a learning rate of 0.1. The classification loss L is measured using a Cross-Entropy criterion defined as:

$$\mathrm{L} = -\sum_{\mathrm{c=1}}^{\mathrm{n}} y_{o,c}\log(p_{o,c})$$

where n is the number of classes and p the predicted probability of observation o being of class c.

All ResNet models employ batch normalization (BN) [20] for faster learning and to avoid exploding gradients. BN has proven to increase neural network generalization performance [21], significantly speed up the training process by allowing the use of larger learning rates, and reduce the need for other methods which often give up important information, such as Dropout [22].

V. RESULTS AND DISCUSSION

The results of the experiments are highlighted in the confusion matrices in Tables I – III. The confusion matrices indicate the classification results for each class and the accuracies as discussed below.

TABLE I. CONFUSION MATRIX FOR GENDER CLASSIFICATION

Actual Gender/Estimated Gender	Female	Male	Acc (%)
Female	273	96	73.98
Male	87	282	76.42

TABLE II. CONFUSION MATRIX FOR HAND CLASSIFICATION

Actual Hand/Estimated Hand	Left	Right	Acc (%)
Left	850	50	94.44
Right	67	833	92.56

TABLE III. CONFUSION MATRIX FOR FINGER CLASSIFICATION

LI	*RI*	*LL*	*RL*	*LM*	*RM*	*LR*	*RR*	*LT*	*RT*	*Acc(%)*
138	2	5	6	20	0	0	1	8	0	76.67
2	**142**	1	1	1	17	3	1	0	12	78.89
6	1	**130**	7	8	0	25	1	2	0	72.22
11	3	7	**127**	4	1	1	25	0	1	70.56
17	0	5	1	**136**	0	10	5	6	0	75.56
1	15	1	2	2	**125**	6	25	0	3	69.44
1	0	24	0	25	1	**118**	8	3	0	65.56
8	3	4	15	7	16	6	**120**	0	1	66.67
5	0	1	0	3	1	1	0	**169**	0	93.89
0	4	0	0	0	0	0	0	0	**176**	97.78

The Table III column subheads are shown below:

- LI denotes Left Index finger
- RI denotes Right Index finger
- LL denotes Left Little finger
- RL denotes Right Little finger
- LM denotes Left Middle finger
- RM denotes Right Middle finger
- LR denotes Left Ring finger
- RR denotes Right Ring finger
- LT denotes Left Thumb finger
- RT denotes Right Thumb finger

- Acc(%) denotes Accuracy (%) for the corresponding class in the tables row.

Our CNN model achieves an overall accuracy of 75.2% on gender classification. As indicated in Table I above, a total of 282 male subjects were correctly classified with 76.42% success rate. While 87 male subjects were wrongly misclassified as females, we hypothesis this is due to some of the male little fingers size being much more similar to that of female subjects. Furthermore, 273 female subjects were correctly classified as females, with a success rate of 73.98% classification accuracy, while 96 female subjects were wrongly misclassified as male. This might also be due to the size of both the male and female middle and little fingers. The sizes and shapes look almost similar and that might make it challenging for the model to correctly classify them. However, having more data for the training will help in reducing the misclassification. This is because some of the features that differentiate the fingerprint images by gender will be learned by the model during the training process.

Similarly, the model performs better in the classification of hands (left or right), with a total accuracy of 93.5%. As highlighted in Table II, the model classified and identified left hands with a high accuracy of 94.44%, with misclassification of 50 left hands identified as right hands. This might be as a result of the orientation of the captured fingerprint images. The fingerprints were captured using various angles of the scanner, as it depends on where the subject stands before the scanner for capturing. Moreover, 833 right hands were correctly classified, with 92.56% overall classification rate, where 67 right hands were wrongly misclassified as left hands.

In Table III, individual subjects' fingers are classified with an overall accuracy of 76.72%. The left and right thumb achieves high classification rate, with 93.89% and 97.78%, respectively. This is for the reason that the majority of the thumb fingerprints occupies a larger portion of the scanner and has less background contents. The worse classified fingers are the left and the ring fingers, with accuracy levels of 65.56% and 66.67%, respectively. The model misclassified and confused the left little and left middle fingers with left ring finger. The right middle finger was misclassified across all the ten fingers category apart from the left thumb finger, similarly, right ring finger was confused with almost all the ten fingers apart from left thumb finger; this might be in connection with the various orientation of the fingers presented before the scanner suspect search during the capturing process.

Fingerprints play an important role in the identification of an individual using their unique features. The CNN learned the good features automatically, by utilizing a broadly used learning methodology based on deep neural networks [19], which have proven to be efficient learning systems. This makes it better in terms of high performance in the detection and identification of gender, hands and fingers related classification issues. However, the fingerprint images used have a lot of background and are not centered, coupled with lack of enough data for the deep networks to learn.

Much of the success of the methodology presented in this paper in classifying gender, hand, and individual fingers, is attributed to the use of TLDA. By using a pre-trained model capable of identifying a wide range of salient features, fine-tuning the pre-trained models was much faster than training using a random weight distribution. Moreover, due to the use of BN, the models did not require a lengthy fine-tuning process.

VI. Conclusions

Fingerprint gender classification helps in classifying and differentiating between genders. We proposed using CNNs and transfer learning in this paper for gender, hands and fingers classifications. Our proposed method achieves promising results. The results of the classification obtained serve as benchmark results for our publicly available SOCOFing corpus. To facilitate the training and benefit from transferable features learned by a model in a different domain, we employed TLDA and ResNets for fingerprint classification. The employed CNN model presents a novel method for hands and finger classification, with an overall classification accuracy rate of 75.52% in gender, 93.5% in hand and 76.72% in finger classification. The usage of this technique can be considered as a main method to be used in order to reduce the suspect search list and time by forensic investigators, as fingerprints remain the most reliable option for personal identification accepted in the courts of law.

In future work, we will extend the method by using some other publicly available fingerprint datasets, with less background content as well as centered fingerprint images. We will also attempt to improve the classification of gender and fingers by introducing the use of minutiae points in the fully connected layer along with the fingerprint features extracted by the convolutional layers. Moreover, we will explore whether other factors such as fingerprint thickness or valley thickness can assist in improving the classification performance of deep CNN models.

More datasets will also be considered as CNNs need high volume of data to learn from. We will also explore the possibility of skin grafting, where individuals cut one part of their finger skin and place it onto another: this may be by switching the grafted skin from a male to female skin, or from left hand to right hand, or even switching between the fingers.

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