Applications of Fingerprint Classification using Deep Learning

Abstract

Fingerprints are the most used authentication systems for biometric security; they can be used to distinguish individuals themselves, but they can also further be used for gender classification. In investigations, gender classification can reduce the time by identifying whether male or female and eliminating excess verification; furthermore, it helps even during gender impersonation. We used Convolutional Neural Network (CNN) to classify gender, hands, and fingers. Furthermore, the liveness of the fingerprint. For these liveness, gender, hands, and fingers classifications, our model obtained an accuracy of 88.1%, 66.2%, 61.2 % and 61% respectively. The model is trained, and the results are based on the Sokoto Coventry Fingerprint Dataset (SOCOFing).

I. Introduction

Fingerprint has been the basic form of authentication for a long time now. From vaults to smartphones, fingerprints were once the epitome of biometric security. However, there have been new ways to counterfeit the security system. A security system needs to be updated constantly in order to be really secure. Although fingerprints are unique and do not change over time[1].

The period of biometric fingerprints to unlock smartphones is shifting over to face recognition systems since they can be hacked using other imitations of fingers[2]. This happens irrespective of the gender, identifying the gender is another gate to bypass in order to increase the security. Understanding the difference between a real and fake finger will amplify the safety. In addition to liveness, being able to detect heartbeat is another measure that can ensure better security.

Apart from personal security, such methods can also help in the identification of suspects. Identification of gender reduces time consumption, detecting the hand as well as finger makes the process faster which otherwise consumes a lot of time investigating improbable suspects'. Such systems not only help in identifying criminals, it can also help detect the cases of gender impersonation, importantly crime impersonation where forgery of credentials such as passport, driver license is done by skilled criminals[3].

In our work, CNN is proposed for various classifications such as liveness, gender, hand as well as fingers using the publicly available SOCOFing dataset. Further, CNN is also applied to identify the level of alteration done to fingerprints for counterfeiting the system. The report is organized as follows: Section II consists of literature review of various studies, Section III has our objectives for this project, Section IV contains the details regarding the dataset, Section V is theoretical background which can be considered as necessary prerequisite knowledge, Section VI describes the methodology briefly, Section VII

II. Literature

The Fingerprint classification problem has be studied and experimented by many scholars over years, using different architectures and methods to perform various applications of the fingerprint classification.

Shehu et al. [4] implemented a convolution neural network performing the task to classify real fingerprints from the altered ones. They also extended this to a multiclass classification problem of identifying the level of alteration that is done on the real fingerprints data i.e., obliteration, central rotation and Z-cut. Their architecture obtained an accuracy of 98%.

Shehu et al. [6], also applied transfer learning technique based on the convolution neural network on the previous study and performed a gender classification task from the real data using Mobilenet Architecture, achieving an accuracy of 75% on the task.

Gender Classification based on on fingerprints was also proposed by [7], which identifies the gender of the convict that helps reduce the search time during an investigation. Their study analyzed a data of 10 fingerprints from 2200 people of different gender and age using various feature extraction techniques. The CNN model implemented by them obtained an accuracy of 88% .

Finally, Convolution neural network models are proven to be powerful in image classification problems. The study [4] explained that CNN's can be used to perform fingerprint classification and produce high performance results. Therefore, a more comprehensive fingerprint classification using top-end feature extraction techniques will provide much more remarkable results in gender, finger and alteration classification tasks. Transfer Learning is also effective in performing these tasks, which was implemented using Mobilenet with pretrained weights from ImageNet.

III. Objectives

The main objective of our work is to explore different applications of fingerprint classification using Deep learning models.

IV. Dataset

Sokoto Coventry Fingerprint Dataset (SOCOFing) consists fingerprints of 600 people. Fingerprints of each finger are collected summing it to a total of 6000 images. From this pool of 6000 images, 4770 belong to male and 1230 belong to female subjects[7]. Using various alteration methods and the extent of alteration; they are classified into easy, medium, hard, consisting of 17931, 17067, and 14272 images respectively. For liveness detection, 6000 real images and 2000 images from each alteration level (easy, medium, hard) are combined to form a subset of 12000 images.This dataset is divided into 80% for training and 20% for testing. Secondly, for gender classification, only a subset of 1230 images from male subjects are chosen randomly, along with all of the female data for data balance. Next for finger classification, images from altered data containing information regarding the first 400 people are chosen as training data and the real images of the remaining 200 people are chosen as testing data. Lastly, to predict the extent of alteration, all the images from the three sets (easy, medium, hard) are grouped. The dataset is split into 80% for training and 20% for testing.

V. Theoretical Background

Alterations of three different levels: obliteration, central rotation, Z-cut is applied on real images using STRANGE toolbox over three parameters settings namely easy, medium, hard. Obliteration is basically the distortion produced, examples of this alteration are abrasion, cuts, etc. Central Rotation appears when the patch,even from other fingers is replanted in place with a rotation. Z-cut is a complex process consisting of three steps: making a Z-shaped cut on fingertip, lifting and switching two traingular skin patches, and stitching them back together.

Convolution is a mathematical operation on two functions (f and g) that produces a third function (f ʘ g) that expresses how the shape of one is modified by the other. Integration of the product of the two functions where one function is flipped and shifted over the other function.

$$f \otimes g = \int_i f(\tau) * g(t-\tau)\, d\tau \qquad \forall f, g \in \Re^1$$

$$f \otimes g = \int_i \int_j f(i-\tau_1) * g(j-\tau_2)\, d\tau_1 d\tau_2 \qquad \forall f, g \in \Re^2$$

Expressions of 1D and 2D convolutions

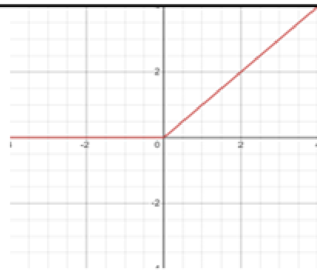
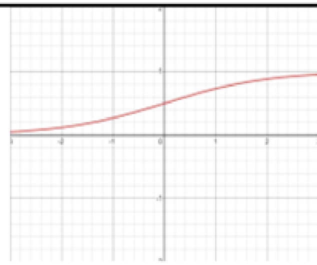
Convolutional Neural Networks is a network which learns through convolution. It is used in image processing since the processing part of CNN is specifically designed to process pixel data. Given an input image I and a filter kernel K with $\times$ dimensions, their output can be summarized as:

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

Max Pooling returns the maximum value from the portion of the image covered by the kernel.

Avg Pooling returns the average of all the values from the portion of the image covered by the Kernel.

Activation functions are used to project the linear data and introduce non-linearity into data.

Function Name.	Graph of Function	Function Equation	Range of function
RELU		$f(x) = \max(0, x)$	$[0, \infty)$
Sigmoid		$f(x) = \frac{1}{1+e^{-x}}$	$[0,1]$

VI. Methodology

Convlution neural networks are the deep learning algorithms, which take an input image and extract features from the different aspects of the image. A CNN model can successfully capture the spatial and temporal dependencies in the input image with the help of different filters and sizes. This abilities of CNN's made them suitable for especially image classification tasks. MobileNet is a CNN model in which the conventional convolution operation is replaced with the combination of Dept-wise convolution and point-wise convolution. This special "dept-wise separable" feature reduces the parameters and computations, which can be efficiently deployed in computationally constrained devices.

Transfer learning and domain adaptation (TLDA) combined can promote the training process by using transferable features learned by the deep learning model and adapting the model to a different source domain. In our work, we applied TLDA to MobileNet and weights are taken from the ImageNet, which has over one million images across 1000 classes, the applied convolutional filters have the ability to extract all types of salient features, which makes them appropriate for feature extraction in other domains, such as gender and finger identification using fingerprint images.

For the four classification tasks at hand we implement a simple CNN model consisting of convolution layers with tuned parameters and a transfer learning based MobileNet model. The training set of the SOCOFING data consists different data and class labels based on the respective classification problem. Both the models are utilized with batch normalization and dropout layers to avoid gradient exploding problem and overfitting. The models are compiled using Adam optimiser with learning rate 0.001 and a categorical crossentrpy loss function to deal with the multiple classes in the data. Different callback methods such as EarlyStopping by monitoring Validation accuracy, ReduceLROnPlateau to reduce learning rate when the monitored metric doesn't change and TensorBoard to visualize the related plots while training the model. The use of these callback from tensorflow make necessary adjustments while the model is executing without human intervention.

VII. Experimental Results and Discussion

1) Gender Classification:

Tabel I. CNN Confusion Matrix

Actual gender/estimated gender	Female	Male
Female	193	61
Male	109	129

Table II. MobileNet Confusion Matrix

Actual gender/estimated gender	Female	Male
Female	183	71
Male	122	116

2) Finger Identification:

Tabel I. CNN Confusion Matrix

Actual Finger/Estimated Finger	LT	LI	LM	LR	LL	RT	RI
LT	112	26	10	17	5	19	2
LI	32	94	31	7	8	5	9
LM	15	29	81	37	15	6	8
LR	18	4	22	100	11	19	11
LL	4	3	5	4	172	3	1
RT	24	6	2	11	1	116	22
RI	3	12	8	12	2	33	95
RM	1	11	4	6	2	11	15
RR	4	3	1	7	0	6	3
RL	0	0	0	0	2	0	1

Table II. MobileNet Confusion Matrix

Actual Finger/Estimated Finger	LT	LI	LM	LR	LL	RT	RI
LT	103	19	11	19	7	22	6
LI	32	81	26	6	12	6	14
LM	22	25	58	30	18	8	21
LR	26	7	15	85	16	18	18
LL	2	5	5	3	67	3	4
RT	41	6	3	17	0	90	14
RI	12	21	15	14	4	22	79
RM	6	22	10	4	8	11	27
RR	8	10	3	8	3	5	5
RL	0	1	2	1	3	0	8

3) Liveness Detection:

Tabel I. CNN Confusion Matrix

Actual Liveness/estimated Liveness	Fake	Real
Fake	960	235
Real	50	1155

Table II. MobileNet Confusion Matrix

Actual Liveness/estimated Liveness	Fake	Real
Fake	710	485
Real	432	773

4) Alteration Classification:

Tabel I. CNN Confusion Matrix

Actual Alter Level/estimated Alter Level	Easy	Medium	Hard
Easy	3428	20	107
Medium	42	2217	628
Hard	174	928	2310

VIII. Conclusion

Finally, we can conclude that CNN performed better than MobileNet in all the different classifications. To obtain better results in Gender Classification, the dataset should be removed of the class imbalance between the genders. In Liveness detection, additional data such as sweat pores, ridges present in the fingerprint images will help improve the accuracy of the models. The Alteration Classification using CNN has shown promising results. A second model is not implemented in this classification due to limited resources. Improving the Quality of the data and employing Ridge detection to extract features in Finger Identification will help model to achieve high accuracy.

IX. Future Work

We can extend this by taking up the publicly available datasets with less background content and centered fingerprint images, We can also improve the gender classification with help of minutiae points in the fully connected layer along with the fingerprint features extracted by the convolutional layers along with that we can explore other parameters such as fingerprint thickness, ridges which will help a lot in improving model performance for deep neural networks.

X. References

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