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Convolutional Neural Network for Fingerprint-Based Gender Classification

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Abstract: The demand for demographic data in security applications has increased the need for gender recognition using biometric features such as the face, voice, iris, fingerprint, and so on. There are lots of gender classification research based on face images but there are a few on fingerprints, hence the need to develop a gender classification system using fingerprint images. The fingerprint is the most accurate, distinctive, and dependable biometric feature that can be used for personal and gender identification. Convolution Neural Network architecture of the deep learning approach was used to classify gender from fingerprints of each of the five finger types and the results were compared and evaluated based on the results of the trained model. The trained model was tested with fingerprint sample images of 20 individuals consisting of the five finger types and overall accuracy of 72% was obtained.

Keywords: Biometrics, Convolution Neural Network, Demographic, Fingerprint, Gender.

1 Introduction

Human biometrics is an essential means of identification. It can be used for different applications such as personal identity, personal authentication, video surveillance, security investigation, border control, and so on. The most widely used biometrics include common qualities that relate to an individual's body traits, such as face, iris, and fingerprint (Minaee *et al.*, 2019). Fingerprints are known to be the most accurate and trustworthy evidence for determining a person's identity, age, and also gender. They are employed as a biometric for gender identification since they are distinctive and remain constant over an individual's lifetime (Sahu *et al.*, 2015).

Gender identification is useful in identifying unknown people and providing information that helps with crime scene investigation. It actively contributes to a number of applications, including biometrics, criminology, surveillance, human-computer interaction, and commercial profiling (Jayakala and Sudha, 2021). It is seen as an issue in psychophysical studies, which concentrates on the efforts to understand human visual processing and discover important characteristics that distinguish between male and female (Liew *et al.*, 2016). One of the most fundamental abilities of humans is the ability to identify gender from a person's face, but there is difficulty when dealing with fingerprints. There is a lot of interest in various application areas in extending this capability to machines.

Convolution Neural Network (CNN) is a type of neural network consisting of a number of convolutional layers, pooling layers and one or more fully connected layers in the typical multilayer perceptron (MLP). The major advantage of CNN over the traditional neural network is the capacity to simultaneously extract features, reduce the image dimension, and classify in one network structure (Liew *et al.*, 2016). Feature extraction and classification is done by feature extraction within a single through learning from data samples. Feature selection is also a part of the training process through learning of weights which does feature extraction.

This research classifies gender into male or female from fingerprint using Convolution Neural Network (CNN). The contributions of this work are to develop a network architecture for gender recognition from fingerprint using CNN, and also reducing the input size, the number of feature maps and the number of layers, thereby improving the performance of the system.

2. Literature Review

Fingerprint recognition can be used for three different applications namely the minutiae structure-based classification, finger information-based classification, and gender classification (Rim, Kim and Hong, 2020). The minutiae structure-based classification classifies fingerprint images into different groups according to finger patterns like arch, loop, and whorl (Win *et al.,* 2019). Finger information-based classification, fingerprint images are classified into finger types and finger states. Finger types include the thumb, index, middle, ring, and small finger on both the left and right hands while finger states are wetness, scar and fragment. Fingerprint is classified as either male or female in gender classification.

For the minutiae structure-based classification, a deep learning approach for classifying fingerprints, known as the SqueezeNet model, was proposed by Gan *et al*. (2019). A total of 2000 fingerprint pairs of NIST-DB4 fingerprints with 512 X 512 resolution was used. First, the gradient approach was used to extract the region of interest (ROI) and the features were then retrieved using the SqueezeNet model, which was divided into five categories: arch, tented arch, left loop, right loop, and whorl. An accuracy of 95.73% was achieved with the transfer learning technique used. Michelsanti *et al.* (2017) used two CNN models to classify fingerprints into the four categories of arch, left loop, right loop, and whorl using NIST SD4 fingerprint database. The transfer learning method which uses the pre-trained weights of the VGG19-F model which is used for fast processing and VGG19-S model used for slow processing were trained on an NVIDIA GTX 950 M GPU using the CuDNN library, for 140 epochs. For the VGG19-F and VGG19-S, the training processes took about 9 hours and 30 hours, respectively, and an accuracy of 94.4% and 95.05% respectively was obtained.

The finger information-based approach was proposed by Shehu *et al.* (2018). CNN transfer learning approach was used to classify hands and fingers. A total of 3000 left-right hand images and 600 images for each of the 10 fingers for fingers classification was used for the research. The collected fingerprint images were later kept publicly at Sokoto Coventry Fingerprint Dataset. The training and classification of the hand and fingers was done using the ResNet model of the deep learning technique and an accuracy of 93.5% and 76.72%, respectively was achieved. Another finger information-based approach was proposed by Kim *et al.* (2020). Five deep neural networks which are CNN, AlexNet, VGG, ResNet and YoloV3 was used to classify fingerprint images into either left or right hand. CNN, AlexNet, VGG and ResNet was trained on the Python platform using the TensorFlow framework while YoloV3 was trained on the C++ platform using the darknet framework. A total of 9080 fingerprint images were used for training while 1000 images were used for validation. The ResNet model produced the highest accuracy of 96.80%.

Finally, on the finger information-based approach, Kim *et al.* (2019) developed a wet fingerprint classification which uses a deep learning approach. The five deep learning models used in Kim *et al.* (2020) was also used to train and validate 6858 and 1716 images respectively. The ResNet model achieved the highest accuracy of 96.17%.

For gender classification, Shehu *et al*. (2018) used the transfer learning approach of CNN to classify gender. A total of 1230 images of male and 1230 images of female was collected to classify the gender as either male or female. The ResNet pretrained model was used to train and classify the gender from the fingerprint images and it produced an accuracy of 75.2%. Liu *et al.* (2019) proposed a deep learning method to predict male or female from 3D fingerprint-images. The 3D fingerprint images were captured by Optical Coherence Tomography (OCT) from 25 Asian females and 34 Asian males. Classification was done using the ResNet-17 model and an accuracy of 80.7% was achieved.

3. Materials and Methods

3.1. Dataset Description

The SOCOFing dataset downloaded from https://www.kaggle.com/ruizgara/socofing was used. The dataset consists of 6000 images from 600 African individuals. Each individual has 10 fingerprints, and they are all at least 18 years old. Unique characteristics of the SOCOFing include labels for gender, hand, and finger names as shown 2__F_Left_index_finger where “2” is the label, “F” is the gender and the other characteristic means that the finger is the index finger of the left hand.

3.2 CNN Architecture

The architecture of the fingerprint-based gender recognition is shown in Figure 1. It has a total of 7 layers which consists of 2 convolution layers C1 and C2, 2 pooling layers P1 and P2, 2 fully connected layers FC1 and FC2 and 1 classification layer. The input layer takes the fingerprint image of size 96 × 96. The Rectified Linear Unit (ReLu) activation function was used at the convolution and pooling layer while the softmax activation function was used for the classification layer. Max pooling method was used at the pooling layer and this performs the feature extraction and the dimensionality reduction. The total number of trainable parameters is 2,369,826. Table 1 shows the output shape of each of the layers and the number of trainable parameters.

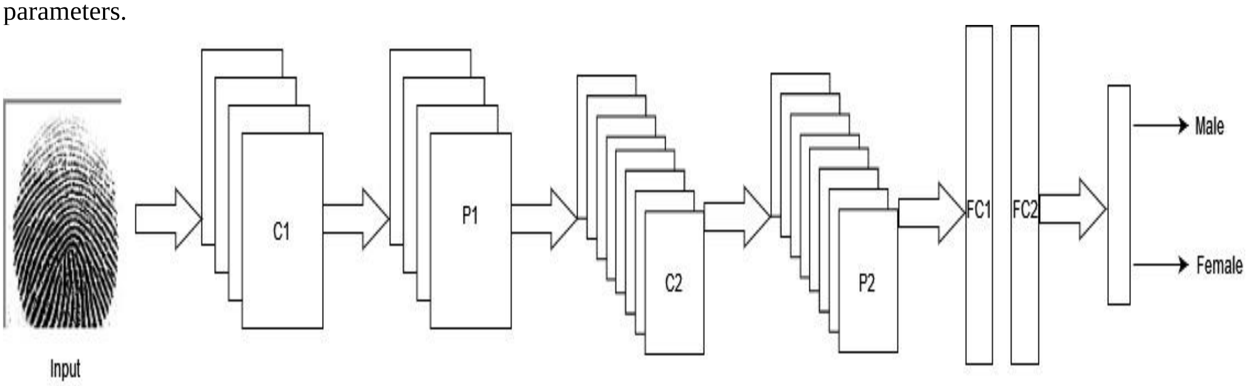


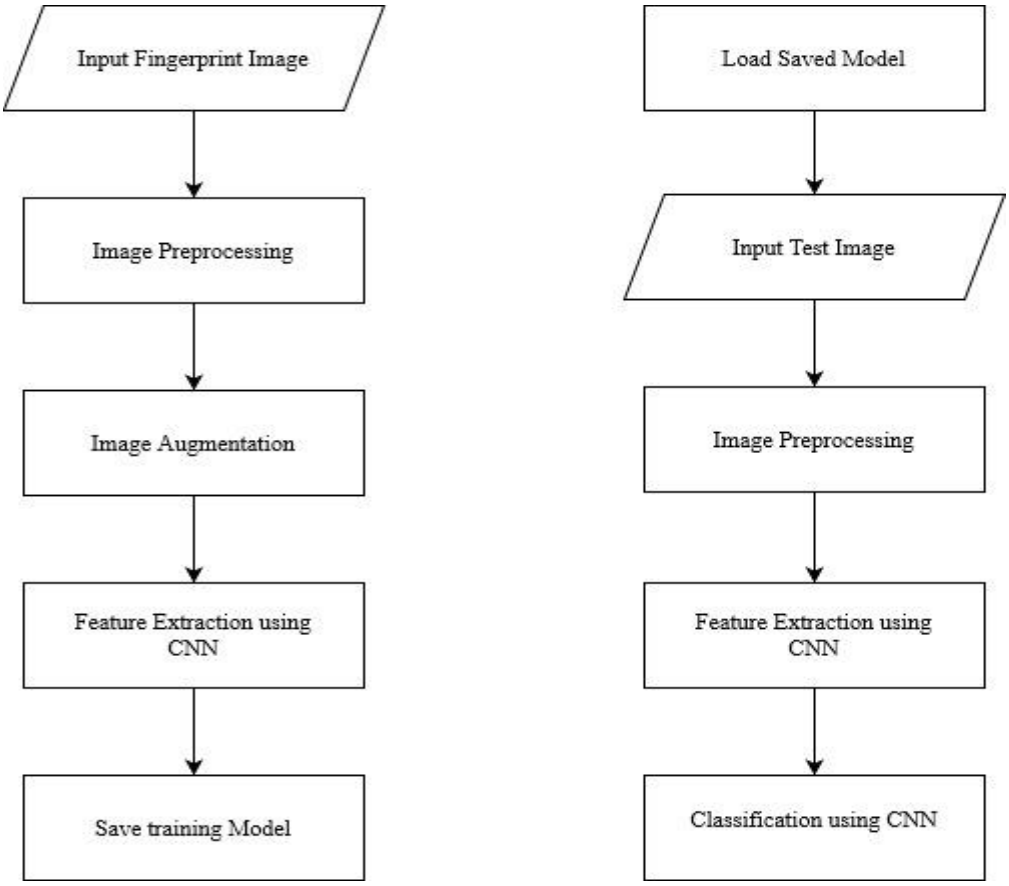
Figure 1: CNN Architecture of the fingerprint-based gender recognition

Table 1: Output shape of the CNN layers
Model: sequential

Layer (type)	Output Shape	Param #
C1	(None, 96, 96, 32)	896
P1	(None, 48, 48, 32)	0
C2	(None, 48, 48, 32)	9248
P2	(None, 24, 24, 32)	0
FC1	(None, 128)	2359424
FC2	(None, 2)	258

3.3. Flowchart of the developed System

The flowchart of the developed system is shown in Figure 2. The model consists of two stages, the training stage and the testing stage. A total of 1200 images was used for training while 300 images was used for testing. The testing images was used for validation. The fingerprint image was acquired from the SOCOFing database. The acquired image was preprocessed and augmented. Augmentation helps to increase the number of images to avoid the problem of underfitting as CNN needed large number of datasets for training. The augmented images were later fed into the CNN classification model for feature extraction and Classification. The pooling layer does the feature extraction while classification was done by the fully connected layer. The CNN classifies the image into either male or female.



Training Stage Testing Stage

Figure 2: Flowchart of the developed fingerprint-based gender classification system

A total of 1500 images were used for training and testing. The images were partitioned into training and testing. A total of 80% of the training image i.e., 1200 fingerprint images was used for training while 20% i.e., 300 fingerprint images was used for testing. Fingerprint images of 150 individuals were used which consists of the left and right fingers. The training phase uses a total of 120 individuals while 30 individuals was used for the testing phase. The training parameters used are epoch of 30, batch size of 64, learning rate (lr) of 0.001, adam optimizer and the loss used is categorical crossentropy. Figure 3 shows the graph of the training showing training accuracy and validation accuracy.

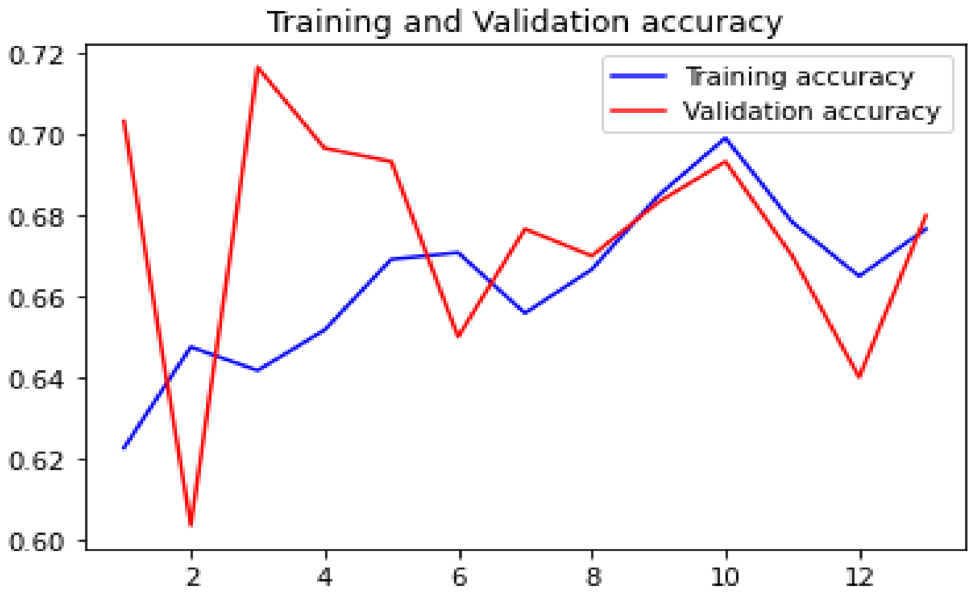


Figure 3: Training graph showing the training and validation accuracy

4. Results and Discussion

The developed fingerprint-based gender classification system was tested using CNN classifier on SOCOFing dataset. The model was developed with Python and tested on an Intel core i7, 16GB RAM computer. CNN was used to classify the fingerprint images into either male or female. A total of 300 samples was used to test the developed model consisting of 150 images each for male and female. The system produced an accuracy of 73% for male, with 110 correct classifications, 70% for female with 105 correct classifications giving a total accuracy of 72%. The confusion matrix is shown in Figure 4 while the classification report showing precision and recall is shown in Table 2.

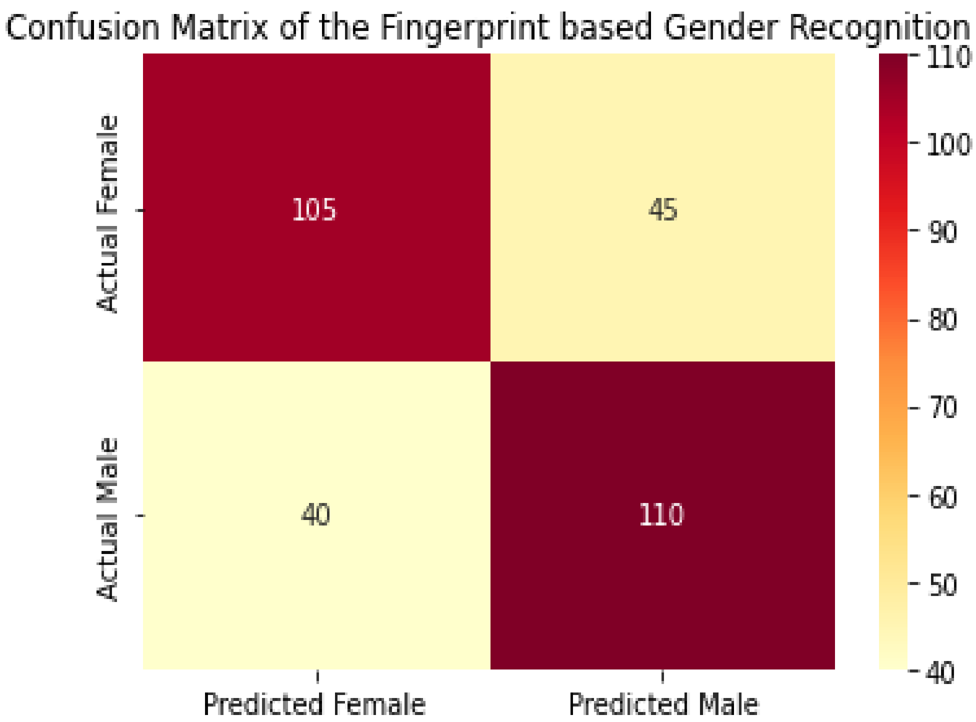


Figure 4: Confusion matrix of the Fingerprint-based Gender Recognition

From Figure 4, a total of 45 female fingerprint images was wrongly classified as male and 40 male samples were wrongly classified as female.

Table 2: Classification Report of the developed model

	Precision	**Recall**	**F1-score**	**Support**
Female	0.72	0.70	0.71	150
Male	0.71	0.73	0.72	150
Accuracy			0.72	300
macro avg	0.72	0.72	0.72	300
weighted avg	0.72	0.72	0.72	300

5. Conclusion

A fingerprint-based gender classification system was developed using CNN. The SOCOFing dataset were used. A total of 1200 images was used for training while 300 was used to test the developed model. The system classifies the input fingerprint image into male or female and an overall accuracy of 72% was obtained. The research showed that CNN can be used to classify fingerprint images into male or female.

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