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Fingerprint Recognition using Deep Learning

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ABSTRACT

Validity and consistency of fingerprint recognition has proven to be one of the most reliable methods for human identification. The fingerprint matching issue is conceived as an arrangement in which a model is created to learn to distinguish between a true and impostor pair of fingerprints. Previously, they used to exercise feature extraction prior to comparing a pair of fingerprints. Also, recently CNN has presented marvelous success for many images processing task. However, there are only a couple of attempts to develop a complete CNN method to influence challenges in the fingerprint recognition problem. We attempted to build a CNN-based fingerprint matching system in this research. The ability to learn fingerprint patterns directly from raw pixels in photos is a significant contribution of the technology. Incomplete and partial pairs of fingerprints were considered for feature extraction in order to achieve resilience and characterize commonalities broadly.
Keywords — MobileNet v1, ReLu Activation, Convolutional Neural Network, Deep Learning

I. INTRODUCTION

Fingerprint is the impression the finger leaves on any surface. It is created due to the friction between the surface and the papillary edges of the finger. Fingerprints are highly unique and have distinguishing features such as grooves and edges that are differently arranged in each individual. This consistency and uniqueness served as an inspiration to use these small but efficient features for human recognition, verification and security purposes. Fingerprint recognition is an automated way of identifying an individual by processing the fingerprint and comparing the extracted features with another fingerprint. This procedure has become popular due to its reliable uniqueness and ease of acquisition.

With development in technology, Biometrics was introduced as an automated way of establishing the identity of a person. Fingerprint recognition provided the basis for this technique.

Fingerprint matching takes in only the required patterns of a fingerprint. Fingerprinting serves as a base for the first forensic professional organization formed, the International Association for Identification (IAI), in 1915. The distinctiveness of the fingerprints made it the most widely used biometric identifier in the 2000s. For authentication reasons, recognition algorithms compare previously saved fingerprint templates to an individual's fingerprints. To do so, either the original image and the individual's image must be directly compared, or certain attributes must be compared. The uniqueness and difficulty of altering the fingerprints of a human and the durability over the life makes them suitable as long-term markers of human identity.

II. RELATED WORK

Biometric Recognition Using Deep Learning: A Survey

Deep learning-based models have been masterful in accomplishing results in computer vision, speech recognition and natural language processing tasks in the last few years. These models have been an essential for steering the ever-increasing scale of biometric recognition problems, from cellphone authentication to airport security systems. Deep learning-based models have progressively been leveraged to enhance the accuracy of different biometric recognition systems over the last few years. For each biometric system, we first introduce the available datasets that are widely used in the literature and their characteristics. Biometric features hold a unique place when it comes to recognition, authentication, and security applications. They won't be able to get lost, unlike token-based features such as keys and ID cards and they cannot be forgotten. Furthermore, it is almost impossible to perfectly imitate or duplicate a fingerprint. Even though recently there have been attempts to generate and forge various biometric features, there have also been methods proposed to distinguish fake biometric features from authentic ones. Fingerprint constitutes ridges, grooves and valleys, forming unique shapes and patterns. Fingerprints have major local portions called Minutiae which can be used to determine the uniqueness of the fingerprint, it has two most important ones that are: ridge endings and ridge bifurcations. The summary of the recent deep learning-based models (till 2019) for biometric recognition. As opposed to the other surveys, it provides an overview of most used biometrics. Deep neural models have demonstrated better and efficient working over older models for various biometrics.

Comparison of Deep Learning Model for Biometrics based Mobile User Authentications

In this paper, Narsi Reddy, Ajita Rattani and Reza Derakhshani describe how deep learning technique provides developments in many applications like image identification, segmentation and other detections. They have elaborated how CNN is a class under artificial neural networks generally used in analyzing visual images, like the ones in camera-based mobile biometrics. We learned how the CNN method employs an input and output layer, as well as numerous hidden layers that include convolutional layers, pooling layers, fully connected layers, and normalizing layers. They compared several CNN architectures like VCG, ResNet, MobileNet V1 and V2, DenseNet and then proposed a model inspired by Mobile Net-v1. However, Mobile Net-v1 intrigued us for our study. They have briefly explained the popularity of Mobile Net-v1 deep learning architecture among mobile-centric They explained that the basic idea behind MobileNet is that instead of utilising standard convolution filters, they use convolution filters of size 3x3, the operation uses a 3x3 convolution filters split into depth-wise separable, followed by convolutions layer having resolution of 1x1. As a regular convolution, this provides the same type of filtering and combination technique. The new architecture, on the other hand, employs fewer stages and parameters.

Fingerprint Recognition Algorithm by Farah Dhib Tatar

In this paper, Farah Dhib Tatar mentions that the advantage of biometric identification is that each individual has their own physical characteristics that distinguishes them from others. This is what makes this type of recognition more reliable. She says that the techniques of fingerprint recognition are enormous and diversified, and are generally based on generic algorithms and tools. The article proposes a fingerprint recognition chain based of Filtering algorithms. The outputs for these algorithms are retrieved and validated using MATLAB. The results acquired are directly connected to two main criteria: the captured image quality and the processor used to process the images. There are many types of sensors used for image acquisition the widely used sensors in the market are the CMOS sensors as they allow to decrease the overall price of cameras, since they possess all the elements needed for the composition of cameras. With regard to the implementation of code, there are various categories of processors that can be used ranging from those provided by companies specialized in embedded manufacturing such as Altera, Xilinx, Texas Instrument etc. Or "free" processors such as Raspberry Pi, Beaglebone, Arduino, etcetera. The software performance and the code remain strongly dependent on these two steps and changes mainly in accordance to the types of processors used for the processing of the image.

III. ALGORITHM

- Convolutional Neural Networks (CNN) has proven to be effective at image classification techniques, that includes classic problems like handwritten digit recognition. The CIFAR-10 and CIFAR-100 algorithms provide state-of-the-art solutions to real-world problems like facial recognition, pose estimation, gray-scale image colorization, and many others.
- Each convolutional layer is made up of a bank of filters (also known as weights) that are convolved with the preceding layer's output or the input image if it is the first layer to produce a reaction.
- The max-pooling layer selects the maximum value in a MxM window to conduct sub-sampling on the outputs provided by the previous convolutional layer or layers. All max-pooling layers in this work are 2x2 with a stride of 2, lowering the output size by 2.
- Fully Connected Layer: This layer connects a group of neurons to each of the previous layer's neurons.

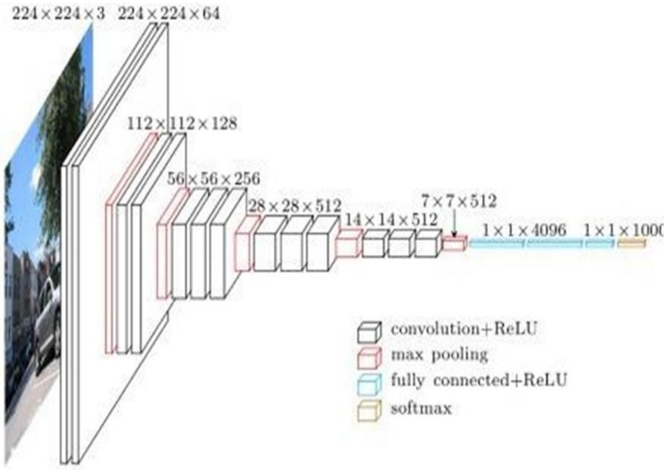


FIG 2.1 CNN ARCHITECTURE

IV. METHODOLOGY

This Project, a setup of Keras, which is an open source Deep Neural Network system with the TensorFlow backend which is utilized to assemble and prepare the Convolutional Neural Network. In the frontend development of this study, for a framework that employs the Python programming language, we created an MVC. This system includes a generator that creates MVC folder structures quickly and easily, as well as the Bootstrap framework and the fact that it is open source. At backend, we have used google collaborator for running the python code, as it gives quicker TPU and RAM size of 12gb for the quicker preparing measure.

In our study of fingerprint recognition, we have collected a dataset containing 600 unique fingerprints that belongs to 60 different people i.e., 10 fingers from each individual along with their personal details like name, age, address, etc. We have taken this dataset from Kaggle. On implementing the Mobile net-v1 architecture of CNN algorithm in our study, we split the data into train set (having 80% of data) and test set (having 20% of data). In the CNN model algorithm generation, firstly we have performed data cleaning, then implemented the Convolution Layer, where each layer has a set of filters that are convolved with the previous layer's output or the input image if it's the initial layer to produce a response. For the first surface, we have set filter to 32 and eventually increased it up to 128 at third layer in the Conv2D() function. We have used layer activation as a parameter of Conv2D function, the activation used is ReLu which applies the rectified linear unit activation function. Then we have implemented Batch Normalization to stabilize the layer. Then we used MaxPooling2D(), which reduced the output size by 2 by making all max-pooling layers 2X2 with a stride of 2.

Model: "SubjectID_Mod"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 92, 92, 32)	832
batch_normalization (BatchNo	(None, 92, 92, 32)	128
max_pooling2d (MaxPooling2D)	(None, 46, 46, 32)	0
conv2d_1 (Conv2D)	(None, 42, 42, 64)	51264
batch_normalization_1 (Batch	(None, 42, 42, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 21, 21, 64)	0
conv2d_2 (Conv2D)	(None, 19, 19, 128)	73856
batch_normalization_2 (Batch	(None, 19, 19, 128)	512
max_pooling2d_2 (MaxPooling2	(None, 9, 9, 128)	0
dropout (Dropout)	(None, 9, 9, 128)	0
flatten (Flatten)	(None, 10368)	0
dense (Dense)	(None, 256)	2654464
dropout_1 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 600)	154200

Total params: 2,935,512
Trainable params: 2,935,064
Non-trainable params: 448

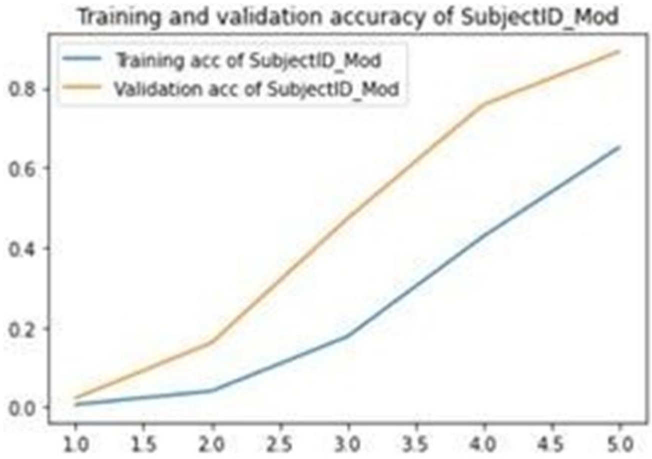
FIG 3.1 MODEL SUMMARY

In the training model, we have set the epoch value to 5 and noticed an increasing accuracy as expected.

```
Epoch 1/5
616/616 [==============================] - 539s 875ms/step - loss: 6.4267 - accuracy: 0.0067 - val_loss: 6.1533 - val_accuracy:
0.0229
Epoch 2/5
616/616 [==============================] - 513s 834ms/step - loss: 5.7654 - accuracy: 0.0404 - val_loss: 5.0455 - val_accuracy:
0.1613
Epoch 3/5
616/616 [==============================] - 495s 804ms/step - loss: 4.4031 - accuracy: 0.1770 - val_loss: 3.2537 - val_accuracy:
0.4726
Epoch 4/5
616/616 [==============================] - 550s 892ms/step - loss: 2.8016 - accuracy: 0.4279 - val_loss: 1.7271 - val_accuracy:
0.7579
Epoch 5/5
616/616 [==============================] - 492s 799ms/step - loss: 1.6543 - accuracy: 0.6510 - val_loss: 0.8840 - val_accuracy:
0.8911
```

FIG 3.2 TRAINING RESULT

On subjecting all the above implementations, a graph is plotted depicting the training and validation accuracy of the subject's fingerprint ID recognized successfully and the loss incurred.



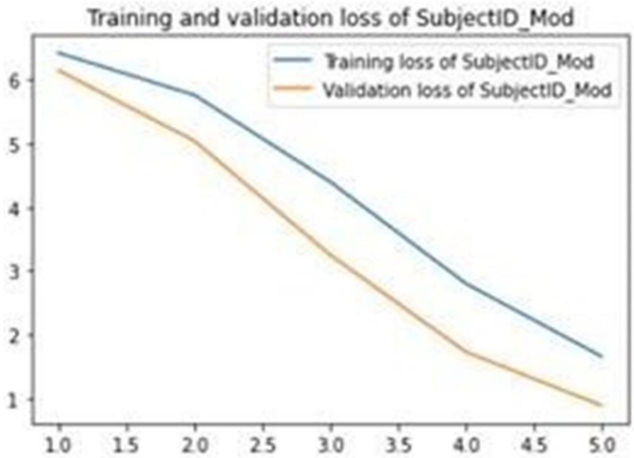


FIG 3.3 GRAPH OF ACCURACY DEVELOPED AFTER TRAINING

V. CONCLUSION

Many features in a human body can be considered as a unique identifier in bio metrics. We have proposed a unique mark acknowledgement in which we venture for separating fingerprint features before implementing CNN classification. The model is supposed to identify a fingerprint image, recognize the print, clean the pattern and differentiate the grooves and edges in the fingerprint. Then, load each fingerprint which is unique to the system along with the details as to whom it belongs to so that it can be later searched and retrieved from the system when an image is uploaded to the system.

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VI. REFERENCES

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