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Fingerprint analysis for age estimation using deep learning models (ResNet50 and VGG-16)

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Abstract--Automatic detection of age from biometric traits is gaining attention from researchers due to its application in many fields. Even though substantial work has been carried out for finding the age using face, gait and speech, very few efforts have been made using fingerprint. This is because of the complexity of extracting distinguishable features. In our proposed work, a ResNet50 model is trained and tested by a fingerprint database namely, house database of digital fingerprint, which contains 1000 images of size 103×96 where 900 are training images, and 400 are testing images. By this model, we have estimated the age of a person under four groups such as 1-8, 9-15, 16-25, 25-60. Experimental results reveal the efficiency of the proposed approach.

Keywords--biometric, fingerprint, age group, deep learning, ResNet50.

Introduction

Unique finger impression is a biometric which contains edge and valley designs as displayed in figure 1. These examples are utilized to address a finger and is called as an epidermis portrayal of it. Like any remaining biometric highlights, for example, face, stride, iris and so forth, unique mark designs are framed as a blend of hereditary and regular components and it shifts between sexes, moral gatherings and age classifications. This sort of development is called as dermatoglyphics and is generally utilized in measurable human studies in view of exceptional nature don't change all time the existence of an independently. Finger impression is a generally acknowledged biometric technique as it is one of a kind,

in any event, for indistinguishable twins. So it is utilized in different administration applications including policing, schools, emergency clinics, banks, private administration and so on. Unique mark based age assessment will be a helpful methodology for those working in criminological framework to zero in just on the anticipated age bunch, which can further develop the pursuit speed and proficiency of the recovery framework by limiting the resulting looking through space. Age information is vital to give scientific prompts tracking down obscure individual.

Unique mark matching techniques, for example, small details based matching strategy and picture based matching technique has been proposed as of late. In any case, particulars based technique contains broad pre-handling steps and furthermore steps expected to decrease the quantity of bogus details, incorrectly distinguished in loud finger impression pictures. Then again, Image based approaches are applied straightforwardly onto the dark scale finger impression picture without pre-handling, thus this strategy accomplishes preferred computational productivity over seemingly trivial details based technique.

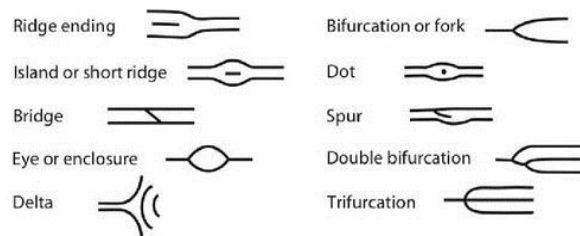


Fig 1. Fingerprint characteristics

Related Work

Eyub broach Ceyhan and Sinan tatoglu [1], introduced age estimation by fingerprint analysis to analyse illegal people from the infraction scene which is a critical issue in decrease the subjects in forensics science. They have used fingerprint features such as ridge thickness, ridge density to valley dencity ratio for age classification. In this study in order to perform the task, they have collected a dataset of fingerprint images covering different age groups and applied KNN (K-nearest neighbor) model for automatic age estimation from fingerprint and achieved 93.3% accuracy. Javier galbally et al. [2], used fingerprint to estimate different age groups such as, children, adults and elderly by estimating the variation of genuine matching score (GMS) difference between the age role. The purpose of this experiment is to complete if the age of an individual can play a role of performance in a biometric system. Zakariya qawakneh et al. [3], developed an automatic age estimation approach from real-world face image using deep learning models. In their proposed work, the first model used was CNN and another model was deep CNN on a database containing face images. They proved that deep CNN model perform better than CNN and achieved 93% accuracy in age estimation.

Anil K jain et al. [4], introduced a model for fingerprint recognition of young children. This model evaluated the achievement of state-of-the-art automated fingerprint recognizing system (AFIS) on child fingerprints, and investigated the persistence of child fingerprint recognition accuracy using statistical models. Jude ezeobiejesi et al. [5], performed latent fingerprint image quality assessment. In this work, the author proposed a deep learning model for latent fingerprint image quality assessment to eliminate the need for manual feature mark-up. The latent fingerprint expert manually marked the region-of-interest, and used the ROI's to search large databases for a reference fingerprint and identified a small number of hidden matches for manual examination. Shixing chen et al. [6], proposed a novel convolutional neural network (CNN)-based framework, CNN-ranking for age estimation. The ranking-CNN contains a set of basic CNN where each one is a trained model in age estimation. Different from the age regression or the multi-class classification approaches, each basic CNN in ranking CNN can be trained in all databases. The performance evaluation of ranking-CNN achieved superior result in age estimation.

Arulkumaran T et al. [7], proposed a 2D discrete wavelet transform (DWT), and principal component analysis (PCA) for age estimation using fingerprint images. In this work, they combined 2D-discrete wavelet transform and principal component analysis to estimate age of a person. The fingerprints of different age groups vary in size and pattern and thickness of ridges and valleys. The algorithm was implemented in optical scanned prints using a good classification algorithm like neural network. Veronica Almedia et al. [8], proposed a soft-biometrics system for automatic age detection from facial images. The first step is preprocessing, to enhance feature extraction. The next step is parameterization, where techniques like wavelet is used. Xinhua Liu et al. [9], proposed a in this work, by transforming the output layers, merging classification and regression age estimation methods, and highlighting important features by preprocessing images and data augmentation methods. Deep learning to dominate the field of artificial intelligent in traditional Convolutional Neural Networks (CNN). In this paper we have implemented deep convolutional models for estimating age from fingerprint images. The architecture and experimental results of these models are discussed in the following sections.

Proposed Work

In this substantial, ResNet50, a deep learning model is used to estimate the age group of a person using fingerprint image. It is a well-known model applied in Computer Vision applications. The ResNet50 model use the architecture as shown in figure 2.

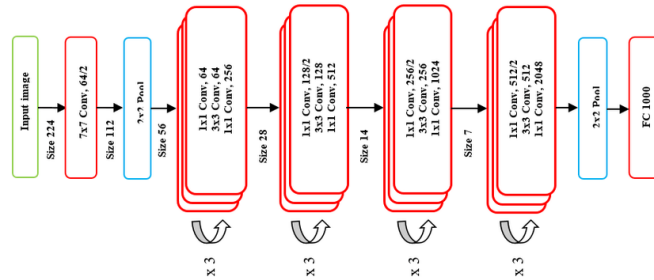


Figure 2. Architecture of ResNet50

Resnet50

This Resnet50 is otherwise called as Residual network is a commonly used model in CNN to identify mapping by shortcuts. Residual Networks comprises of various successive residual modules, which are the basic foundation blocks of ResNet. As the network goes deeper and deeper, the training is more challenging. Generally, the input feature map will be followed by the convolutional filter, non-linear activation function and a pooling operation and finally the output layer. Here, back multiplication algorithm is implemented. As the network goes deeper and deeper, it is hard to converge. The input size of the image is 224 x 224 x 3. Every ResNet structure makes the first convolution and max pooling using 7 x 7 and 3 x 3 kernel sizes distinctively. Next, first stage of the network commences and it comprises of 3 Residual blocks containing 3 layers each. The size of the kernels utilized to perform the convolution operation with all 3 layers of the block of the first stage is 64, 64 and 128 respectively. The curved arrows refer to the identity connection. The connected arrow represents that the convolution operation in the Residual block is executed with stride 2, therefore, the size of input will be decreased to half in relation to height and width but the channel width will be doubled. For each residual function F , 3 layers are stacked one over the other. The three layers are 1x1, 3x3, 1x1 convolutions. The 1x1 convolution layers are responsible for decreasing and then replacing the dimensions. The 3x3 layer remains as a bottleneck with less input/output dimensions. Finally, the network has an average pooling layer by a connected layer with 1000 neurons since this model is pre-trained for different ImageNet database classified for 1000 classes.

VGG-16

VGG Net is abbreviation for Visual Geometry Groups Networks. This model is one of the most powerful deep convolutional neural networks which has proposed by Simonyan et al. This part depicts the VGG-16 profound CNN model for characterization old enough assessment utilizing profound CNNs whose engineering is displayed in figure 3. This model comprises of 13 convolutional layers with 3x3 channel size, five subsampling/max pooling layer with a size of 2x2, and two completely associated layers with initiation work and Soft-Max work. Convolutional layers eliminate features from the data pictures.

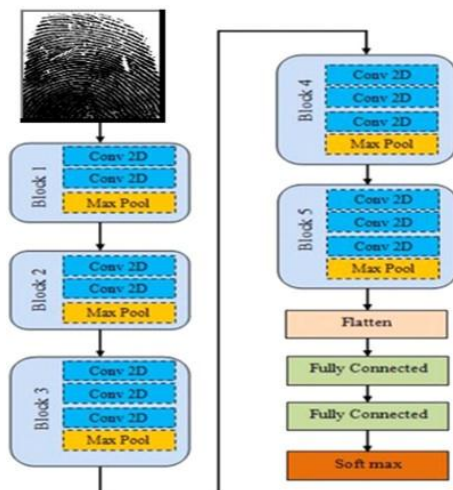


Figure 3. VGG 16 Architecture

The 13 convolutional layers are appropriated in five squares. The underlying two squares contain two convolutional layers in each square. Other three squares comprise of three convolutional layers in each square. The primary square convolutional layer extricates the low-level provisions like lines and edges. More elevated level layer removes the undeniable level elements. Each convolutional layer channel has a part size of 3×3 . The channel size of the convolution is bit by bit expanded from 64 to 512.

Experimental Results and Analysis

Dataset

The house database of digital fingerprint dataset are collected from the kaggle. There are different types of age group fingerprints in four classes: 1-8, 9-15, 16-25, and 25-60. The sample fingerprint images in the database are shown in figure4.

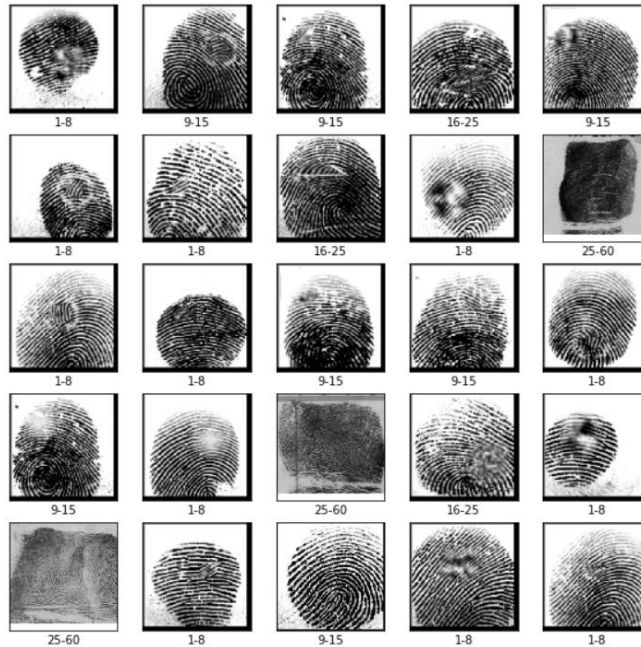


Fig 4. Sample input images of Fingerprint

In this work, we exploit the fingerprint images for age estimation using deep learning model ResNet50. 1000 images are used for training and 200 images are used for testing the model. The ResNet50 model was trained by fine-tuning hyper parameters namely dropout probability from 0.1 to 0.5 and achieved better performance for dropout probability 0.4. Out of 200 test images the ResNet50 classified correctly 185 fingerprint images. Therefore, the accuracy of ResNet50 is 93%. One sample output image is shown in figure 6.

Sample output

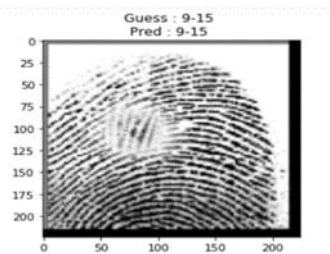


Figure 5. Classified output

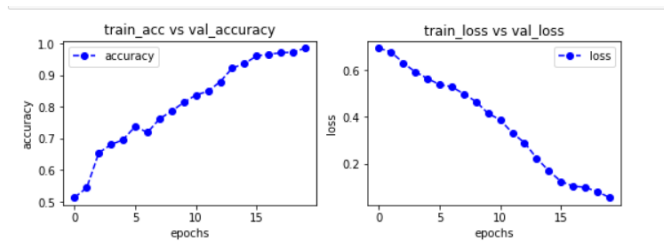


Figure 6. Accuracy and Loss Diagram of ResNet50

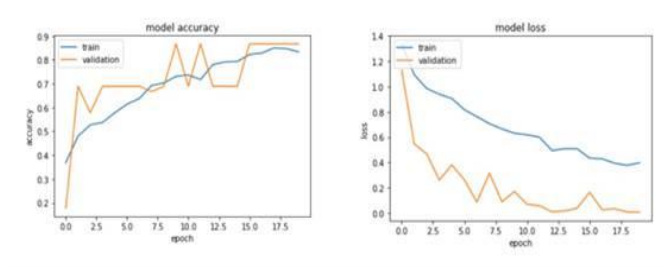


Figure 7. Accuracy and Loss diagram of VGG-16

Confusion metrics- Confusion metrics in table 1 and table 2 is used for summarizing the performance of our classification algorithm where the number of correct and incorrect predictions are summarized

Table 1
Confusion Matrix of ResNet50

Age group	1-8	9-15	16-25	25-60
1-8	93	0	0	0
9-15	1	90	0	1
16-25	0	0	92	1
25-60	0	2	0	91

Table 2
Confusion Matrix of VGG-16

Age group	1-8	9-15	16-25	25-60
1-8	93	0	0	0
9-15	1	90	0	1
16-25	0	0	92	1
25-60	0	2	0	91

Performance metrics such as Precision, Recall, Accuracy and F1-score are calculated using equation (1) to equation (4).

$$\text{Accuracy} = \frac{\text{Total no.of correct prediction}}{\text{No.of input samples}} \quad (1)$$

$$PRE_i = \frac{TP_i}{TP_i + FP_i} \quad (2)$$

$$REC_i = \frac{TP_i}{TP_i + FN_i} \quad (3)$$

$$F_1^i = \frac{PRE_i \times REC_i}{PRE_i + REC_i} \quad (4)$$

Is the number of times the classifier correctly identifies the positive class as positive (TP). The number of times the classifier correctly predicts the negative class as negative is referred to as True Negative (TN). The number of predictions where the classifier mistakenly identifies the negative class as positive is referred to as false positive (FP). The number of predictions where the classifier mistakenly predicts the positive class as negative is referred to as False Negative (FN).

Table 2
Performance Metrics of the proposed approach

Deep learning model	Accuracy	Precision	Recall	F1-score
ResNet50	93	91.5	93	92
VGG 16	85	89.5	90	88

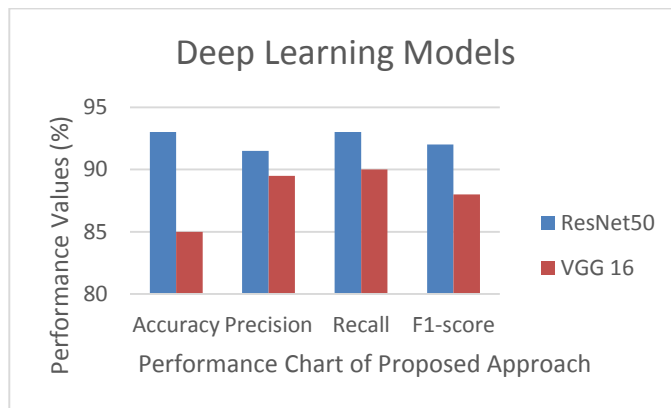


Figure 8. Performance chart

Conclusion

In this paper, deep learning model Resnet50 act used to estimate affect age group of a person using fingerprint. We have trained the model using images from house database. The model attained 93% of accuracy. This will be helpful for crime crime investigators to minimize the number of suspects and also for the anthropologists to estimate the age of the fingerprints obtained from excavated articles.

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