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Special Issue

Finger Knuckle Biometric Authentication using Convolution Neural Network

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Abstract--To ensure security of confidentiality maintained complex systems; biometrics has become the most efficient solution, which refers to the automatic identification of a person based on their physiological or behavioral characteristics. This paper proposes a Biometric Authentication system using deep learning concepts, where the finger knuckle of the user is considered to enhance the security of the system. This model can recognize an authorized user based on major finger knuckle pattern using Convolution Neural Network (CNN) and extracts the features and are optimally compared with the trained images. The CNN is trained by back propagation algorithm with stochastic gradient descent and mini-batch learning with the help of Neural Network Toolbox in MATLAB, which can provide accurate output than any other algorithms used for authentication.

Keywords--Biometrics, Finger knuckle biometrics, major finger knuckle, CNN.

I. INTRODUCTION

Biometrics refers to technology with automated methods which can scientifically authenticate a system using biological factors. It considers the physiological or behavioral characteristics of human being as a method of verifying personal identity. Physiological characteristics refer to the features which are extracted from human body such as fingerprint, face, retina, palm print, iris and DNA whereas behavioral characteristics such as voice, gait, signature and keystroke. Among which physiological characteristics are used widely in systems like e-banking, network security system, ID card [1].

Recently it is found that finger-knuckle is also a biometric factor which can be used for a secure authentication system. Initially this system goes under local feature extraction and then a combination of local and global feature extractions are made which is followed by geometric feature extraction and finally an improved acquisition device where both major and minor inherent knuckle skin pattern can be used to distinctly identify the personality [2].

In this paper, considering the major knuckle print as the biometric factor, the authentication of a system is done. Fig. 1 shows the major finger knuckle image to an acquisition device. Considering the accuracy, deep learning method, is the best suitable for this authentication.

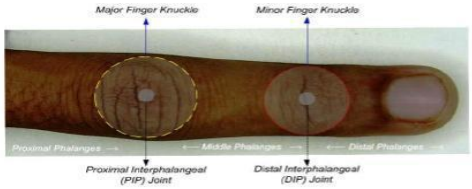


Fig. 1 Finger Knuckle [18]

In Deep learning algorithms the output is obtained only after the transformation of the input, through different layers. This multi-layer network has each two adjacent layers connected to each other in some way. Input provided will undergo certain changes while they are transferred from one layer to other. Among all the deep learning algorithms, Convolutional Neural Network (CNN) is the best algorithm, which gives more accurate output for the designed authentication system [3].

Convolutional neural network is an artificial neural network inspired by the animal visual system, consisting three major layers; Convolutional layer, pooling layer and fully connected layer [3]. CNN is capable of extracting features without losing much spatial correlations of the input. With neurons in every layer, having learnable weights and biases. In this work, CNN is trained by back propagation algorithm with stochastic gradient descent and mini-batch learning with the help of Neural Network Toolbox in MATLAB.

Rest of this paper is organized as follows: section 2 deals with related works, section 3 deals with the CNN

architecture, section 4 deals with the proposed system and section 5 deals with experiment and results.

II. RELATED WORK

Mourad chaa et al. [4] proposed a biometric based personal authentication system using finger knuckle print of the user. The ROI of the finger knuckle images are analyzed using 1D-Log Gabor wavelet to extract the preliminary features and then Gabor filter bank is applied on the preliminary features to discriminate the features for enhancing the discriminatory power. Finally LDA is used for dimensionality reduction. Matching process is done by Nearest Neighbor classifier which uses cosine Mahalanobis distance. Analysis is done using 165 samples, but the proposed method failed to give high accuracy.

Using these set of points recognition is done with the optimized convex model. Each image is considered as a class and for recognition of each class the closest geometric distance between the convex hulls (The point set boundary) is considered. The reliable convex hull is constructed for the classification using an appropriate nonlinear fitting model with the kernel method of SVM. However, the proposed method has some limitations (i.e.) if the shortest distance between the convex hulls is equal then it leads to recognition fail.Abdallah Meraoumia et al. [7] developed a Finger-Knuckle-Print identification based on Histogram of Oriented Gradients and SVM classifier, where the features are considered as vectors and are extracted by using Histogram of Oriented Gradients and multi-class Support Vector Machine algorithm is used to train the system, which gives higher identification rate and less classification error and proposed that combinations of four finger images at score level provides better result.

However, the reliability and efficiency of the existing algorithms has to be further verified and there are many key technical issues which have to be solved. The proposed method gives better accuracy when compared to the existing algorithms

III. CNN ARCHITECTURE

CNN are made up of neurons that have weights and biases. It is different from regular neural network because it has neurons arranged in three dimensions namely width, depth and height. CNN is widely used because it is proved to be very successful for large scale image classification [9 10 11] as it goes deep layer by layer. They have been used in various computer applications such as image classification, object detection etc [12]. Their performance is mainly based on concepts such as local connections, shared weights and the use of several hidden layers [13]. There are few hidden layers in CNN namely input layer, convolution layer (CONV), ReLU layer, pooling layer (POOL) and fully connected layer. Various images of Finger Knuckle have been trained through several hidden layers. The input layer consists of the input image. CONV layer follows the input layer and extracts different levels of features and activation map is also generated from the input image. RELU layer follows CONV layer and it checks if the pixel values is less than zero, if so it performs thresholding at zero. POOL layer follows CONV layer [13], when filter slides over image we get sub regions and the function of POOL layer is to output the maximum value in each obtained sub region after using a filter. Lets us see the operations of each layer in detail. Fig 2 shows sample CNN architecture.

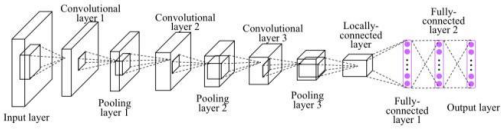


Fig 2 CNN Network

. INPUT LAYER:

The input layer contains the original size of the given input image and holds the raw pixel values of the image with three color channels R, G, B. This layer also has the ability to perform various other operations like data augmentation, random flipping or cropping of the data, or data transformation.

B. CONVOLUTIONAL LAYER:

The Convolutional layer (CONV) follows the input layer that will compute the output of neurons which are connected to the local regions in the input, each computing a dot product. This layer makes use of two important features namely “filters” and “strides”. Filters are nothing but a set of weights which are applied to a region in the image. Filters slide over image spatially computing dot products and it also extends to the full depth of the input volume. The step size with which filters moves along the image is stride. There can be different strides, but sometimes we might go wrong with choosing the number of strides. In such a case, the formula to obtain the correct number of stride is

(N-F)/strides+1,

where **N** is the dimension of the convolutional layer and **F** is the dimension of the filter. For example when N=7, F=3 and when we use a stride of 1, in the formula (7-3)/1+1=5, The number of filters determines the number of activation maps. Another important feature is padding. The reason why we use is padding when filters slide over the image we obtain activation map whose dimension is lesser than the original image, so when many filters are

used, the dimension of the activation map obtained goes lesser and lesser and hence it does not work well. To overcome this defect we use padding. Padding makes sure that the dimension of the image remains constant when filters are used. The most commonly used is zero padding. Zero padding is simply adding zeros to the borders of the input image. We can apply zero padding to the vertical and horizontal borders of an input

E. FULLY CONNECTED LAYER:

Neurons in this layer are fully connected and have full connections to all activations in the previous layer as seen in regular Neural Networks. This layer also computes class scores. Their activations are calculated using matrix multiplication followed by a bias offset.

IV.PROPOSED CNN ARCHITECTURE FOR AUTHENTICATION SYSTEM

image and thereby it helps us to control the size of the image. When padding is not used the image gets shrunk and it does not work well. So it is better that we go with the use of padding. The main purpose of padding is to maintain constant size of the image. The formula used for padding is

(F-1)/2

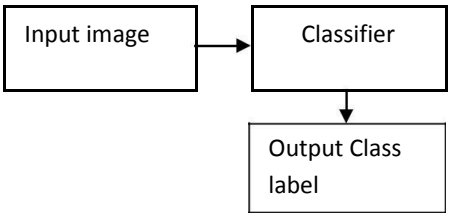
example when filter size F of 7 is used in the formula (7-1)/2 we get 3 which means three zeros must be added to the vertical and horizontal borders of the image in order to maintain the constant dimension of the image.

C. ReLU LAYER:

The ReLU layer (Rectified Linear Unit layer)will apply an element wise activation function on the image such as max(0,x) when it finds that the pixel value is less than zero and hence performs thresholding at zero. Advantage of this layer is that it leaves the size of the volume unchanged. In basic this layer changes all negative activations or negative pixel values to zero.

D. POOL LAYER:

POOL LAYER is also known as Down Sampling layer. The function of the pool layer is to progressively reduce the spatial representation of the image when there are too many parameters because when there are too many parameters it leads to too many computations in the network. Having too many parameters also leads to over fitting of the image .So an important function of this layer is also to control over fitting. There are several pooling operations such as min pooling, max pooling, average pooling, etc., out of which max pooling is the most commonly used one. This layer basically takes a filter and a stride of the same length. When filter is been applied to the input volume, the function of this layer is to output the maximum number in every sub region of the image.



The proposed system uses datasets which are collected from the Hong Kong Polytechnic University. The datasets are resized to 180x180x3 dimension for the convenience of the filter to slide over the input. These Datasets are given into the CNN layers for Training. Designing CNN layer is the most important task in the system .CNN layer should be implemented by adding and reducing layers depending on the training datasets. For example; considering a sample dataset for 20 subjects the proposed architecture contains 9 layers. Input images are given as an input to the Input image layer which is the first layer of the CNN. The output of each layer is given as the input to the next layer.

output with Soft max layer that transforms values to probability. Input image is now given to the already trained network for the classification process and the classification label is obtained. In spite of data the network gives the classification label for each input but in addition to this score value of each label is compared. With the score value of 90% and above this proposed system authorizes the user.

V.EXPERIMENT AND RESULTS
. DATA INTRODUCTION

Contactless Finger Knuckle Images Database (Version 1.0) used in this experiment where taken from The Hong Kong Polytechnic University. This Database contains finger knuckle images of 503 different subjects and these Images were acquired using contactless imaging setup and only Major Finger Images is used in this system. Each subject has 5 images and as a total 2515 images of 180x160x3 dimensions.

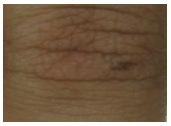


Fig 3(a)

Fig 3(b)

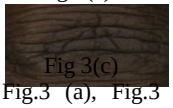


Fig 3(c)

Fig.3 (a), Fig.3 (b), Fig.3(c) shows the Major-finger knuckle image of 3 different subjects. All the images are

provided in *.bmp format and the segmentation algorithm is described in the T-IFS 2014 paper in the cited reference.

B. RESULTS

Results obtained from the proposed system are trained, tested and verified manually in the system configuration of Intel i5 CPU with 2 Core(s), 4 logical processor, 160 GHz processor, 4GB of RAM, 2301MHz in Mat Lab R2017a using Neural Network Toolbox. Total execution time for training 20 samples took around 150 minutes in the above configuration system. When the system is trained using 7 Layers (Input, CONV, ReLU, POOL, FC, SM, CF) with 10 filters it took around 20 minutes and 22Epochs which resulted in 84% accuracy. By increasing the number of layers to 9 Layers (Input, CONV, ReLU, CONV, ReLU, POOL, FC, SM, and CF) and filters to 15 it took around 60 minutes and 30 Epochs which resulted in 97.5% accuracy as show in Fig 4 and Fig 5.

Fig 4 Workspace

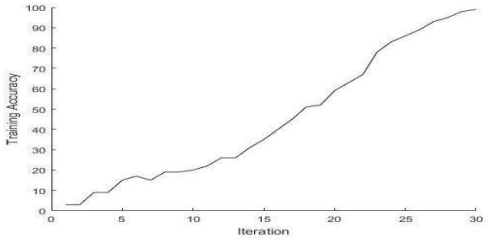


Fig 5 Accuracy

C. CONCLUSION AND FUTURE WORK

This paper has presented a novel work in the field of biometric authentication system based on major finger knuckle pattern. When compared with existing systems with simple classifiers like SVM, PCA, LDA etc. Deep learning provides better accuracy. As a future enhancement, accuracy can be improved by increasing the number of CNN layers and by using GPU with Parallel computing toolbox in Mat Lab the training, testing time can be reduced and real time authentication application can be developed using this approach.

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