Turkish Online Journal of Qualitative Inquiry (TOJQI)

Volume 12, Issue 3, July 2021:2967- 2976

Iris Recognition: A Study of Various Pretrained Networks Approach

Sheena S[1], Sheena Mathew 2[2]

Abstract

A recent development in deep learning techniques. Iris biometrics is the superior and most refined of all biometrics systems. Iris trait is declared as the most powerful tool for human identification because of the strong and unique textual information. This paper concentrate on the importance of the iris feature, which is one of the unique biometric modality. This unique feature of the iris pattern can be extracted effectively using various pre-trained CNN models and analyzed its performance in this work. In iris recognition, the important step is to extract the most prominent features of the inputted iris image. Extracted features of the input iris image learned from the pre-trained network such as VGG16, Inception, ResNet, etc. are evaluated. The input image is initially localized, normalized, and then enhanced, then it will be classified into N classes. The performance of the proposed system is tested on two public datasets viz IITD and CASIA. A high accuracy rate is obtained with this proposed system.

Keywords: *iris recognition, feature extraction, VGG-16, INCEPTION-V3, XCEPTION, deep Learning*

Introduction

Iris recognition emerges as one of the most reliable bio-metrics because its flowery pattern leads to having a unique feature. Due to this unique feature iris recognition is considered to be

[1] Assistant Professor, Cochin University of Science & Technology, Faculty, Computer Science & Engineering Department, School of Engineering, sheenas@cusat.ac.in , ORCID ID

[2]Prof.Dr.,Cochin University Science & Technology, Faculty, Computer Science & Engineering Department, School of Engineering, sheenamathew@cusat.ac.in, ORCID ID

Received: Accepted:

the most secure person identification system with a fewer number of false matches. The reason behind this stability is that the complex flowery pattern remains the same throughout the lifetime of an individual. At the same time, iris biometric is very difficult to be forged. Thus iris recognition assures the highest level of security. Nowadays iris recognition is currently being used as the major authentication system in many countries. In iris recognition, there are mainly three stages viz. Image preprocessing, feature extraction, and template (feature) matching. The iris image dataset consists of a set of eye images, that are to be pre-processed to get the useful part of the iris region. John Daugman was the one who developed the first patented algorithm for iris recognition, and over these years this algorithm remains the basis for the iris recognition system. Nowadays many research has been carried out on this technology and various technology have been exploded and today there is rapid growth in mathematical and hardware aspects in this iris recognition system. Iris recognition has a wide variety of applications in border security, tracking of people, banking, etc. Indian government initiated a Unique Identification Authority of India (UIDAI) scheme known as Aadhaar in which the Indian government enrolling much biometrics including iris patterns of more than a billion residents.

The uniqueness of iris texture comes from the random and complex structures which are formed during the gestation period itself. Image classification is one of the problems in which Deep Learning exceeds tremendously. The goal of image classification is to classify a specific picture according to a set of possible categories. Pre-trained image classification network that has already learned to extract powerful and informative features from natural images and use it as a starting point to learn a new task.

This paper proposes an iris recognition method in which the features are extracted using a different pre-trained network such as GoogleNet, Resnet50, ResNet101, VGG16, VGG19. The performance of the proposed system is analyzed with the extracted features from the normalized iris pattern. This study was conducted with publicly available databases like the IITD iris database and CASIA version1.

The paper is organized as section II Background of convolutional neural network. In section III Related work is described. The proposed iris recognition system is described in section IV. The experimental work analysis and the results are explained in Section V. Finally in section VI conclusion is described.

Frameworks of Convolutional Neural Network

A. CNN

A convolutional neural network (CNN) is a class of deep learning neural networks. CNN has become the most popular tool in computer vision tasks nowadays. Their application to the biometrics field is starting to emerge in various biometric recognition, detection as well as in image segmentation. In a convolutional network, the input is the first argument which is referred to as convolution, and the second argument is the kernel. The output is normally referred to as the feature map. The machine learning system can be improved by utilizing the advantage of convolution. They are sparse interactions, parameter sharing, and equivariant representations. CNNconsists of three different types of layers as detailed in figure1. They are i) Convolutional layer, a layer performing the convolution operation on the input image by using a set of filters known as the kernel. This convolution operation will result in a feature map. ii) Pooling layer, which is used to decrease the size of convolutional layer output. This layer will save the most significant information contained in the input layer. This pooling layer can either max pooling or average pooling. Max pooling is the most popular type. iii) Fully connected layer is the one which is used the extracted features from the preceding layers. This layer will do the classification task.

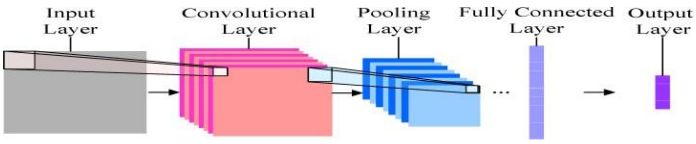

Fig. 1. CNN layers

Different pre-trained networks have gained popularity nowadays. Most of these have been trained on the ImageNet dataset, which has 1000 object categories and 1.2 million training images. ResNet-50 is one such model. This can be loaded using the Resnet-50 function from Neural Network Toolbox. The various pre-trained CNNs are open-sourced and widely used in different applications and show very promising performance in image classification. In this proposed iris recognition system first, the VGG net is used to extract the deep features. It has been tested using two iris dataset IITD dataset and the CASIA version1. The experiment achieved good results with high recognition accuracy. Then the features are extracted from the pre-trained CNN AlexNet model. The performance of this model is evaluated by extracting the features from the normalized iris pattern. AlexNet is the extended version of conventional LeNet. This pre-trained network takes more computational power. The result of tuning the hyper-parameter of this network comes up with high performance. This Alex-net is the first to implement the (ReLU) as the activation function. Another pre-trained network experimented with is GoogleNet/Inception, which is listed with a top-5 error rate of 6.7%.

The inception layer is a combination of all those layers with their output filter blocks stacked into a single output block which will form the input to the next stage. This type of layering results in dimensional reduction. Then parallel Max Pooling layer provides another option to the inception layer. Thus by adding a subsequent layer in the deep learning model will pay attention to the learning of the previous layer. This will recognize the object by selecting the appropriate filter size in each layer. The next pre-trained architecture used is ResNet-50 or Residual Network which is a classical neural network. ResNet architecture is having less complexity than VGGNet. The main goal of the Inception module is that it can act as a multilevel feature extractor. This is done by computing 1x1, 3x3, 5x5 convolutions. From the results it is observed that VGG network is slow to train and also it takes time to deploy. Its network architecture weights themselves are quite large in terms of disk or bandwidth. Wheras ResNet model is a much deeper model and much smaller as 102MB. Training is also faster compared to VGG. When compared with VGG and ResNet Inception model is much smaller as 96MB and computationally efficient.

Related Work

Daugman's pioneered work was considered as the pillar behind the success of iris recognition which happened in 2002 by developing the feature descriptors such as Gabor's phase-quadrant feature descriptors. Gabor phase-quadrant feature descriptor introduced by Daugman is considered the major success behind iris recognition. Initially, this Gabor phase-quadrant feature descriptor, which is named the iris code was the only descriptor that plays a major role in the field of iris recognition. A wide range of descriptors such as Discrete Cosine Transform (DCT) [5], Discrete Fourier Transform(DFT) [10], ordinal measures [16], hierarchical visual codebook [17], etc. for iris were also proposed by many researchers. Recently many authors proposed an iris recognition system using deep learning techniques [8]. The authors Minaee et.al. proposed deep learning structures for iris recognition by utilizing a convolutional neural network which in turn jointly understand the complex features and thus conduct the identification process[11]. Here they extract the deep features using VGG pre-trained network. They have achieved high results with a good accuracy rate. W. Zhang, C. Wang et.al. developed another iris recognition system in which the iris region is in the preprocessing stage. Then that region is divided into eight different rectangular sub-region. This then fed to the CNN model for training [15]. Oyedotun, O. et.al. proposed a system that uses CNN in addition to a deep belief network. They have used LeNet-5 architecture for CNN[13]. Maram G. Alaslani et.al proposed the system in which the features are learned and extracted using pre-trained CNN (AlexNet). Then the classification is done by using the multi-class SVM algorithm.

Proposed System

In this work, we proposed an iris recognition system using the pre-trained network. The recognition system is divided into two stages. In the first stage, the iris portion alone is identified from the input eye image. This has been done using various image processing techniques such as localization, normalization, enhancement, etc. The input image taken from the iris dataset is first localized as in figure2. Before applying the localization procedure some image processing morphological operations are applied. Then the actual localization process will be done. Using Hough circle iris's pupil boundary is found out. The localization procedure will detect the two iris boundaries i.e inner iris boundary and outer iris boundary. This localization process will extract the iris part from the input eye image using Circular Hough Transform(CHT).

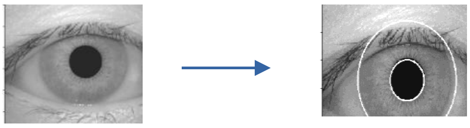

Fig 2: Iris boundaries are extracted using iris localization algorithm

Then this localized image is then normalized[6]. The normalization is done using Daugman's Rubber Sheet Model. This will transform the localized iris image from Cartesian coordinates to polar coordinates as shown in figure 3. The normalization procedure will eliminate the dimensional irregularities which will happen by the stretching of the iris region. Daugman's Rubber Sheet mapping of the localized iris from cartesian coordinates to polar coordinates can be defined mathematically as given below.

$$I(x(r,\theta), y(r, \theta)) \rightarrow I(r, \theta)$$

$$x(r, \theta) = (1- r)\, x_p (\theta)\, r\, x_1(\theta)$$

$$y(r, \theta) = (1-r)\, y_p (\theta)\, r y_1(\theta)$$

In the above mathematical representation, I(x, y) is the intensity value at (x, y) in the iris image. The coordinates are represented by the parameters such as x_p, y_p, x_1, and y_1 are the coordinates of both inner and outer iris boundaries along withdirection[1].

Once the normalized iris image is obtained, its interpretability of information in images can be more accurately identified by applying image enhancement techniques. In our method Histogram equalization method is applied to get a well-distributed texture image. Histogram equalization technique is used for enhancement which is a cumulative distribution transformation function, which will be transforming the input image into an equally likely intensity image. By this image enhancement method contrast of the image will be increased. The normalized and enhanced image is shown in figure4a and 4b.

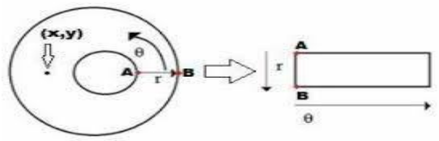

Fig3: Daugman's Rubber Sheet Model of the localized iris image from cartesian coordinates to polar coordinates

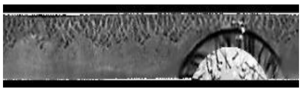

Fig 4a: Normalized image

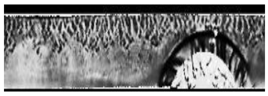

Fig 4b: Enhanced image

Now it is ready for feature extraction and classification. This is the second stage. For feature extraction and classification we proposed to use pre-trained networks. For that various pre-trained networks such as GoogleNet, ResNet50, ResNet101 are tested and analyzed their performance.

Iris Image classification using various pre-trained architecture has experimented and the results were analyzed. The feature is extracted not only from different convolutional layers but also from max pooling, RELU, dropouts, and fully connected layers. This has been accomplished using various pre-trained networks as mentioned in the table below. The algorithm given below explains the steps required for the feature extraction and the classification stages.

//**Input**The input images

//**Output** The Accuracy

1. An input image is loaded
2. Load the pre-trained CNN(GoogleNet, ResNet, etc)
3. Pre-process the images for the pre-trained networks
4. The training set and testing set of images are divided
5. Extract the features from the respective pre-trained networks
6. Training features are identified from the training set
7. Test set features are extracted
8. A trained classifier is used to predict for the test set

9. isplay the accuracy.

Experimental Analysis and Results

The proposed system is tested using two major iris datasets IITD datasets and CAISA Version 1. The specification of the database used is described in the table1 given below. The performance of the system is evaluated using different parameters as shown in the table below. The experiments have been conducted on the pre-processed iris image from the datasets. Resizing the image has been done based on the pre-trained networks used. The localized and normalized images are split randomly into training and testing data. For that 80% of images are used for training and 20% of images are used for testing.

Table 1
Specification of the database used

Dataset	IITD	CASIA
Number of subjects	224	108
Samples per subjects	10	7
Number of images	2240	756
Image formats	BMP	JPG

The features are extracted from the deeper layers of pre-trained networks using their appropriate activation function. The initial feature layer map of the Convolutional Neural Network is shown in figure 5. These layers mainly contain edges and colors. These are the resultant of different edge detectors and color filters available in the respective pre-trained networks used in this work.

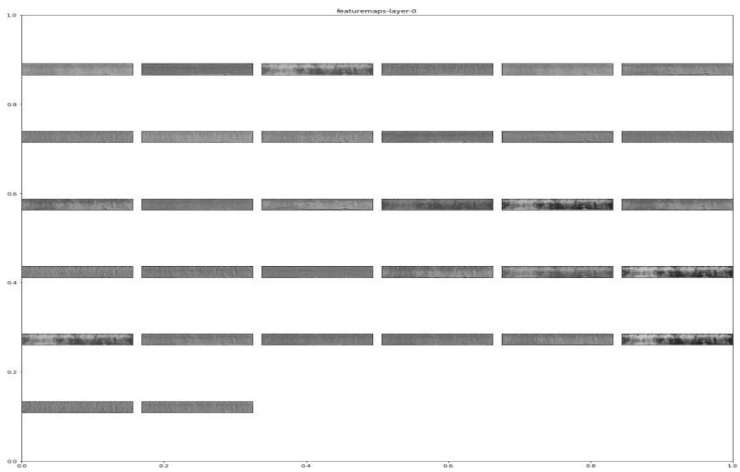

Fig 5: Filters learned on the feature layer map '0'

The various performance parameters such as sensitivity, specificity, etc. to evaluate the efficiency of the different pre-trained DAG networks are elaborated in the given table 2. DAG network is a network with a direct acyclic graph, which has a complex network architecture. This type of network object having one input layer and one output layer. The studies show that the DAG network has the potential to develop to yield a high-performance network. From table 2 it is clear that the selected pre-trained network gives good sensitivity and specificity with a very less error rate.

Table 2

Performance comparison for DAG networks

Parameters	GoogleNet	ResNet50	ResNet101
Number of Epochs	1000	702	123
Train size	1792	1792	1792
Test size	448	448	448
Sensitivity	1	1	1
Specificity	0.9463	0.9956	0.982
Error Rate	0.2941	0.0738	0.154

In this work, we evaluated two different databases IIT Delhi iris database and CASIA Iris by using various pre-trained networks. From the result, it is observed that training loss is very less, which in turn results in good accuracy, which is elaborated in Table 3 given below. In this work, we input the iris to the network after localization and normalization. This helps in reducing the time to capture the necessary and sufficient features.

Table3.

Training Loss of different pre-trained networks

Database Used	Pre-trained Network used	Training Loss
IITD	VGG-16	0.129
	INCEPTION V3	1.5373
	XCEPTION	4.8506
CASIA	VGG-16	0.0116
	INCEPTION V3	2.7545
	XCEPTION	1.8121

Discussion and Conclusion

In this work, we evaluated different pertained networks for iris recognition. This is done by extracting the learned features of the pre-trained network. The input image from the database is initially gone through various image processing operations such as morphological operation, localization, normalization, and image enhancement. This makes it ready for feature extraction, then it is evaluated using different categories of pre-trained networks and analyzed its performance. The only drawback found with this pre-trained network is that its computational complexity is high due to a large number of learned parameters. And also it is a time consuming task requiring an entire network to be trained before it can serve as an initialization for a deeper network.

Acknowledgment

The authors would like to thank IIT Delhi and CASIA for providing an iris database for the research purpose online.

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