

CONVOLUTIONAL NEURAL NETWORK BASED FEATURE EXTRACTION FOR IRIS RECOGNITION

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ABSTRACT

Iris is a powerful tool for reliable human identification. It has the potential to identify individuals with a high degree of assurance. Extracting good features is the most significant step in the iris recognition system. In the past, different features have been used to implement iris recognition system. Most of them are depend on hand-crafted features designed by biometrics specialists. Due to the success of deep learning in computer vision problems, the features learned by the Convolutional Neural Network (CNN) have gained much attention to be applied for iris recognition system. In this paper, we evaluate the extracted learned features from a pre-trained Convolutional Neural Network (Alex-Net Model) followed by a multi-class Support Vector Machine (SVM) algorithm to perform classification. The performance of the proposed system is investigated when extracting features from the segmented iris image and from the normalized iris image. The proposed iris recognition system is tested on four public datasets IITD, iris databases CASIA-Iris-V1, CASIA-Iris-thousand and, CASIA-Iris- V3 Interval. The system achieved excellent results with the very high accuracy rate.

KEYWORDS

Biometrics, Iris, Recognition, Deep learning, Convolutional Neural Network (CNN), Feature extraction (FE).

1. INTRODUCTION

In recent years, the concept of personal identity becomes critical, and the biometrics is a popular way for authentication, which has been considered as the most secure and hardest way for authentication purpose[1]. Biometric systems are developing technologies that can be used in automatic systems for identifying individuals uniquely and effectively and it becomes a good alternative to the traditional methods such as passwords. According to a study published in [1], users choose to use smartphone biometrics as an alternate for passwords because it provides additional safety for new technologies like Apple Pay [1].

Biometrics is an automated technique for authenticating an individual depends on a physical or behavioral characteristic. Physical characteristics like fingerprints, voice, face, and iris. Behavior characteristics are traits which can be learned or acquired such as, speaker verification, keystroke dynamics and dynamic signature verification [2].

Among all unique physical features, iris biometrics is known as the most accurate and impossible to reproduce or replicate [3]. The iris is a visible but protected structure. Also, iris does not significantly change over time, so it is perfect and reliable for identity authentication [3, 4].

Iris recognition system has main stages. First, segmenting the required region of iris, after that it is normalized to be a fixed pattern in polar coordinates. Then, the features extracted from that pattern to be recognized at the last stage [5].

Extracting effective features is the major important stage in a lot of object recognition and computer vision tasks. Therefore, several researchers have focused on designing robust features for a variety of image classification tasks [6].

Nowadays, much attention is given to feature learning algorithms and Convolutional Neural Networks (CCN). In this algorithm, the image is fed directly to the convolutional neural networks, then the algorithm extracts the best features of this image [6, 7].

In this paper, we propose an iris recognition system where the features are extracted from the pre-trained CNN Alex-Net model, and for the classification task, the multi-class Support Vector Machine (SVM) is used. The performance of the proposed system is investigated when 1) extracting features directly from the segmented iris image, and 2) extracting features from the normalized iris pattern. The experimental study is tested on four public datasets collected under different conditions IITD iris databases[8], CASIA-Iris-V1[9], CASIA-Iris-thousand [10], and CASIA-Iris- V3 Interval [11].

The rest of this paper is organized as follows: Section 2, provides a brief background about the basic idea of Convolutional Neural Networks. In section 3, some related works are presented. Section 4, introduces a description of the proposed iris recognition system. The experimental results and analysis are presented in section 5. Finally, the Conclusion is given in section 6.

2. CONVOLUTIONAL NEURAL NETWORK BACKGROUND

Convolutional Neural Networks (CNN) belong to a specific category of Neural networks methods. CNN has not only been able to learn image feature representations automatically, but they have also outperformed many conventional hand-crafted feature techniques [12].

Neural networks models have a hierarchical representation of data and depend on the computation of layers that have a sequential implementation, the previous layers output will be the next layers input. Every layer gives one representation level. And, there are a set of weights that parameterized the layers. Also, the input units linking to output units through the weights in addition to a group of biases [13].The weights in the Convolutional Neural Networks (CNN), are shared locally, which means that each location of the input has the similar weights. The filter form by the weights linked to the similar output [13].

A Convolutional Neural Network (CNN) comprises of alternating layers of locally connected convolutional layers where every layer has the same number of filters. downsampling layers, and the fully connected layers that work as a classifier [14]. Figure 1, shows the overall architecture of a CNN.

Convolutional Neural Networks architecture has three concepts that make it effective: local receptive fields, weights sharing, and downsampling operations [15]. The local receptive field means every neuron accepts input from a small portion of the preceding layer. Also, it has the same size of the convolution filter. Local receptive fields are used in convolutional and

downsampling layers. The weights sharing is applied to the convolutional layer to control the capacity and to decrease the complexity of the model. Finally, the nonlinear downsampling which used in the downsampling layers to decrease the spatial size of the image as well as decrease the number of the free parameters of the model. These concepts help the CNN to be strong and effective in recognition tasks [15]. In more detail, the Convolutional Neural Networks layers are:

The Convolutional Layer: the weights in this layer are made of a set of learnable filters produced randomly and learned through the back-propagation algorithm. The feature map is the outcome of every filter that convolved through the entire image. Also, the feature maps have the same number of the applied filters in that layer [15].

As shown in Figure 1, the first convolutional layer containing 6 filters that produced 6 feature maps which arranged together. Every feature map represents specific features from the image, for example, represented points, or represented vertical edges [16]. The convolution operation is described in (1).

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right) \quad (1)$$

Here j is the specific convolution feature map, M_j is a selection of input maps, k_{ij} is the filter, b_j is the feature map bias, l is the layer in the CNN, and f is the activation function [14]. The ReLU is the common activation function which used to add non-linearity to the network [15].

The Pooling Layer: which implements a downsampling operation to decrease the spatial size of the convolutional layers. First, the size of pooling mask and pooling operation type must be determined and after that applied at the pooling layer [17].

The pooling operation implemented on the pixel values captured by the pooling mask, multiply it by a trainable coefficient, after that added to a trainable bias [14]. The pooling operation is described in (2).

$$x_j^l = f(B_j^l \text{pool}(x_j^{l-1}) + b_j^l) \quad (2)$$

Where x_j^l is the result of the downsampling operation applied on the j^{th} region in the input, x_j^{l-1} is the j^{th} region of interest captured by the pooling mask in the previous layer, pool is the specific operation done on the region (max or average), B_j^l is a trainable coefficient, b_j^l is a trainable bias, and f is an activation function [18]. The max pooling is the most common pooling operation which is used in this paper.

Fully connected layers: which used the extracted features in the preceding layers to do the classification task [19]. The result of the last convolutional or pooling layer is fed to the fully connected layers like in an original neural network [15].

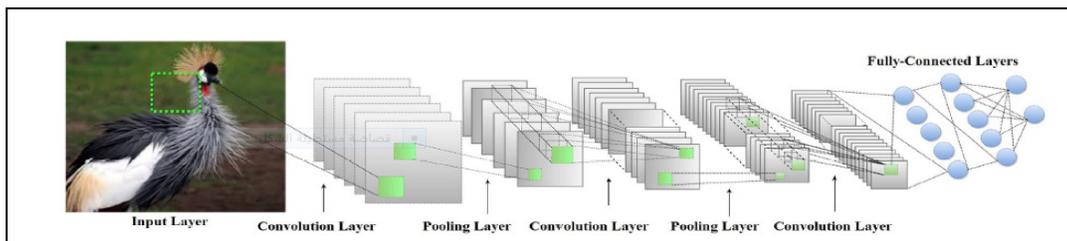


Figure 1. An illustration of the Convolutional Neural Networks architecture. The gray squares mention the feature maps and the green squares mention the convolution filter. The cross-lines among the last two layers mention the fully connected neurons[15].

3. RELATED WORK

Several works have been addressed the use of the Convolutional Neural Network (CNN) for biometric recognition. Some of these works are presented here.

The authors in [5] proposed an iris recognition system where they used the pertained VGG-Net to extract the deep features. Then they used a multi-class SVM algorithm for classification. They tested their system on two iris databases, IIT iris dataset, and CASIA 1000 Iris dataset. Their experiment achieved high results with the accuracy recognition of 99.4%.

The authors in [20] proposed a system for face recognition with strong 4-layer CNN architecture; the proposed system can handle facial images which have facial expressions, poses, occlusions and changing illumination. The results of the experiment showed a high accuracy rate of 99.5% on AR database. Their experiment on the 35-individuals from FERET database shown recognition accuracy of 85.13%.

The authors in [14] proposed a system for the diagnosis of iris nevus depending on a Convolutional Neural Network in addition to deep belief network. Iris nevus is defined as a pigmented growth located around the pupil or in the front of the eye. They used a pertained LeNet-5 architecture for CNN. Their accuracy rates are 93.35% for CNN and 93.67% for the deep belief network.

The authors in [7] proposed an algorithm which uses a convolutional network named scattering transform/network which delivers a multi-layer representation of the signal and is invariant to translation, small deformation, and rotation. After extraction of scattering features, they used the Principal component analysis to decrease the data dimensionality and then recognition is performed using a multi-class support vector machine. Their proposed algorithm has been tested on three face datasets and gives a very high recognition rate.

The authors in [21] proposed a MATLAB-based finger-vein recognition system based on CNN with Graphical User Interface as the user input. To retrain the network for new incoming subjects, they used two layers of CNN out of the proposed four-layer CNN. The pre-processing stages for finger-vein images and CNN design have been conducted on different platforms. They tested the system on 50 images that are developed in-house. The experiment achieved an accuracy rate of 96%.

Table 1. summarize the related work presented in this section.

4. THE PROPOSED IRIS RECOGNITION SYSTEM

The proposed iris recognition system using the Convolutional Neural Network (Alex Net) for feature extraction is shown in Figure 2, The development of the proposed iris recognition system is discussed in three parts: the pre-processing stage, feature extraction stage, and classification stage.

4.1. The preprocessing stage

In this stage, iris segmentation and normalization are performed. In the proposed system, the primary goal of selecting the iris region as an input to Convolutional Neural Network (Alex-net) model as an alternative to the entire eye image, as proposed in [15], is to decrease the computational complexity of the model. An additional goal is to avoid the decline of matching performance as well as the extraction of feature causing by eyelids and eyelashes appearance.

For the iris segmentation process, the circular Hough transform is applied for detecting the boundaries of the iris and the pupil which involve first perform Canny Edge detection to generate an edge map [22]. The Canny Edge detecting contains five stages: Smoothing, Finding, Gradients, Non-maximum suppression, Double thresholding, Edge tracking through hysteresis [23]. Algorithm 1 lists all the required steps for iris segmentation.

For iris normalization process, the rubber sheet model is used. As shown in Figure 3, In this model every pixel within the localized iris area is remapped from Cartesian coordinate (x,y) to polar coordinate (r,θ) where r is on the interval $[0,1]$, and θ is angle $[0,2\pi]$. The representation of mapping the iris region to the normalized polar coordinates can be modeled as in (3) [15, 24].

$$\begin{aligned}
 I(x(r, \theta), y(r, \theta)) &\rightarrow I(r, \theta) \\
 x(r, \theta) &= (1 - r)x_p(\theta) + rx_i(\theta) \\
 y(r, \theta) &= (1 - r)y_p(\theta) + ry_i(\theta)
 \end{aligned}
 \tag{3}$$

Where $I(x,y)$ is the iris area, (x,y) is the original Cartesian coordinates, (r,θ) is the corresponding normalized polar coordinates x_p, y_p and x_i, y_i are the coordinates of the pupil and iris boundaries along the θ direction [15, 24].

The results of the segmentation and the normalization steps are shown in Figure 4.

Table 1. Summary of Using Convolutional Neural Network for Biometric Recognition

| Reference# (Year) | Biometric | CNN Model | Classification | Dataset | Accuracy |
|-------------------|-------------|------------------------------|---|--|---|
| [5] (2016) | iris | VGG-Net | multi-class SVM | IIT iris dataset, and CASIA 1000 Iris dataset | 99.4% on IIT iris dataset 90% on CASIA 1000 Iris dataset |
| [20] (2014) | face | LeNet-5 | classification depends on the winner-takes-all rule | AR database and FERET database | 99.5% on AR database 85.13% on FERET database |
| [14] (2017) | iris | LeNet-5 | multi-class SVM | A free database (The Eye Cancer Foundation, Eye Cancer Network) | 93.35% |
| [7] (2016) | face | scattering transform/network | multi-class SVM | Yale Face Database Georgia Tech Face Database Extended Yale Face Database | 93.1% |
| [21] (2016) | Finger-vein | LeNet-5 | classification depends on the winner-takes-all rule | The database collected in-house using 6 different fingers. There are 60 participants from the Universiti Teknikal Malaysia Melaka. The total is 600 samples. | 96% |

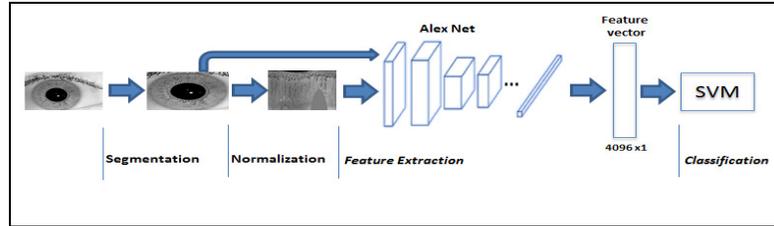


Figure 2. The proposed iris recognition system using Convolutional Neural Network (Alex Net) for feature extraction

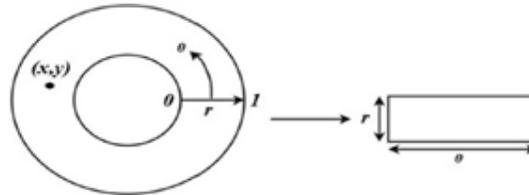


Figure 3. Normalized iris region using the rubber sheet model [15].

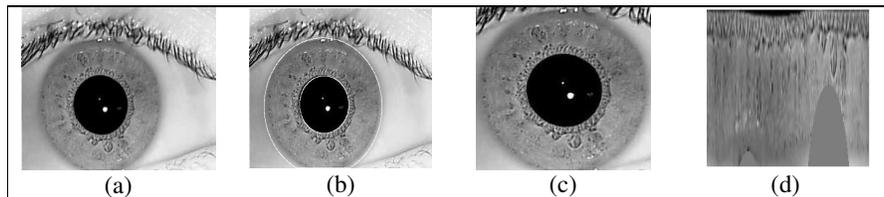


Figure 4. The result of segmentation and normalization stage for (Image 01-L) from IIT Iris Database (a) Original input image. (b) Detected iris and pupil boundary. (c) segmented iris image. (d) Normalized iris image.

Algorithm 1: Automatic iris region segmentation from an eye image.

//Input: The input eye image

//Output: center and radius of iris circle, and center and radius of pupil circle

- 1: Define the range of pupil and iris radius, manually set the range of radius, according to the database used
 - 2: Find the iris boundaries
 - Perform canny edge detection to generate an edge map.
 - a) Apply Gaussian filter
 - b) Apply gamma function
 - c) Apply non-maximum suppression
 - d) Apply hysteresis thresholding
 - Apply circular Hough transform
 - Draw circles of different radius for all edge point.
 - Find the maximum in the Hough space, and it will be the parameters of the circle
 - 3: Find pupil boundary using the same steps but just using the region within the previously detected iris boundary
 - 4: Return the center and radius of iris and pupil circle
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4.2. The feature extraction stage

The pre-trained Convolutional Neural Network model (Alex-Net) is used for feature extraction process. This model was designed by the Super Vision group[25]. Alex-Net is a scaled version of the conventional Le-Net [12].

Alex-Net is trained on the Image-Net Large-Scale Visual Recognition Challenge (ILSVRC). Alex-Net is trained to classify the 1.2 million images in the image-Net database into 1000 different classes. Figure 5 shows the overall architecture of Alex-Net model [25]. It contains set of layers; the input layer is the first layer which defines the input dimensions. The Alex-Net model needs the input image to be 227-by-227-by-3. The middle layers make up the bulk of the AlexNet. These layers consist of series of five convolutional layers, followed by rectified linear units (ReLU) and max-pooling layers. Next to these layers, three fully-connected layers. The classification layer is the final layer [25].

The first convolutional layers perform 11x11 convolutions with stride 4 and with no padding, the second convolutional layers perform 5x5 convolutions with stride 1 and pad 2, The other convolutional layers perform 3x3 convolutions with stride 1 and pad 1, and 2x2 pooling (with no padding). The detailed explanation of Alex-Net layers is shown in Table 2.

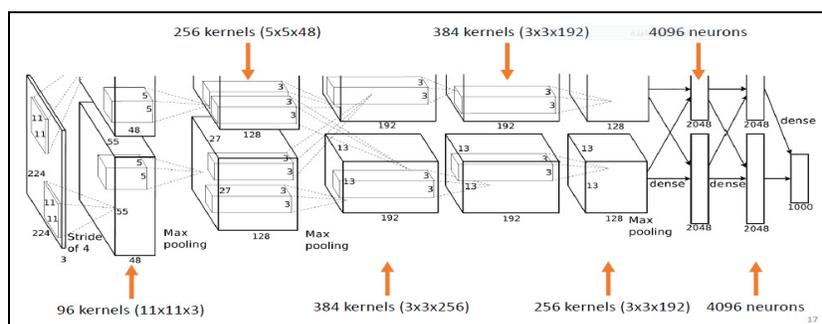


Figure 5. The architecture of Alex-Net model [25]

Table 2. The Detailed Explanation of The Alex-Net Layer

| Type of Layer | No. of Filter | Feature Map Size | Kernel Size | No. of Stride | No. of Padding |
|--|---------------|--|--------------|---------------|----------------|
| Image input layer | | 227 x 227 x3 (height x width x channel) | | | |
| (1st convolutional layer) Relu-1 Cross-channel normalization Max pooling1 | 96 1 | 55 x 55 x 96 27x27x96 | 11x11 3x3 | 4x4 2x2 | 0x0 0x0 |
| (2nd convolutional layer) Relu-2 Cross-channel normalization Max pooling2 | 256 1 | 27 x 27 x 256 13x13x256 | 5x5 3x3 | 1x1 2x2 | 2x2 0x0 |
| (3rd convolutional layer) Relu-3 | 384 | 13 x 13 x 384 | 3x3 | 1x1 | 1x1 |
| (4th convolutional layer) Relu-4 | 384 | 13 x 13 x 384 | 3x3 | 1x1 | 1x1 |
| (5th convolutional layer) Relu-5 Max pooling5 | 256 1 | 13 x 13 x 256 6x6x256 | 3x3 3x3 | 1x1 2x2 | 1x1 0x0 |
| Fully connected layer-6(fc6) Relu-6 | | 4096 x1 4096 x1 | | | |
| Fully connected layer-7 (fc7) Relu-7 | | 4096 x1 4096 x1 | | | |
| Fully connected layer-8 (fc8) Softmax layer Output layer | | 1000x1 1000 class | | | |

4.3. The classification stage

The classifier is needed after feature extraction to find the corresponding label for every test image. Different types of classifiers can be used for this task, for example, Support Vector Machine, Softmax Regression, and Neural Network [26]. In this work, a multiclass Support Vector Machine classifier has been used. A brief description of multiclass SVM is as follows:

Assuming we have the set of training data $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ and we want to classify the set into two classes where $x_i \in R^d$ is the feature vector and $y_i \in \{-1, +1\}$ is the label class. The two classes are linearly separable with a hyperplane $w \cdot x + b = 0$. With no other previous knowledge about the data, SVM can find the optimal hyperplane as the one with the maximum margin (which results in the minimum expected generalization error) [27].

The multi-class SVM can be implemented for a set of data with M classes, we can train M binary classifiers that can distinguish each class against all other classes, then select the class that classifies the test sample with the greatest margin (one-vs-all) [27].

Algorithm 2 lists all the required steps for the feature extraction and the classification stages.

Algorithm 2: Extracting feature using a Pre-trained CNN (Alex-Net) and classify the feature using the SVM algorithm.

//Input: The input images

//Output: The recognition accuracy

- 1: Load input images and its labels
 - 2: Split each category into the similar number of images
 - 3: Load pre-trained CNN (Alex Net model)
 - 4: Pre-process images For Alex Net model
 - 5: Split the sets of the images into training and testing data.
 - 6: Extract Features from the deeper layers of Alex-Net model.
 - 7: Get training labels from the training set
 - 8: Use the training features to train a multiclass SVM classifier
 - 9: Extract features from test set
 - 10: Use the trained classifier to predict the label for test set
 - 11: Get the known labels for test set
 - 12: Tabulate the results by a confusion matrix.
 - 13: Convert confusion matrix into percentage form
 - 14: Display the mean accuracy
-

5. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed system is tested using four popular iris datasets: IITD iris databases [8], CASIA-Iris-V1 [9], CASIA-Iris-thousand [10], and CASIA-Iris-Interval [11]. The iris images are captured in these databases under different situations of pupil dilation, eyelids/eyelashes occlusion, slight shadow of eyelids, specular reflection, etc.

The proposed system performance is evaluated according to the accuracy of the recognition rate. The accuracy is the fraction of labels that the classifier predicts correctly. We tested the system on 60 subjects in each dataset. The specifications of these subjects for the four datasets are summarized in Table 3.

Table 3. The specifications of the used datasets

| dataset | IITD | CASIA-Iris-V1 | CASIA-Iris-Thousand | CASIA-Iris-Interval |
|---------------------|-------------|---------------|---------------------|---------------------|
| Number of subjects | 60 | 60 | 60 | 60 |
| Samples per subject | 10 | 7 | 10 | 10 |
| Number of images | 600 | 420 | 600 | 600 |
| Image size (pixels) | (320 × 240) | (320 × 280) | (640 × 480) | (320 × 280) |
| Image format | BMP | BMP | JPEG | JPEG |

The experiments have been conducted on these datasets in two cases, the first case: using the iris image after segmentation. In this case we resize the image to be 227-by-227 as required for the for Alex-Net input.

The second case: using the iris image after normalization. In the normalization stage, the normalization parameters were set manually, the radial resolution is set to 227 and the angular resolution also is 227. So, the size of the image that comes from normalization stage is 227-by-227, which is suitable for Alex-Net input.

The sets of the segmented and normalized images are split randomly into training and test data. For each person 80% of images are used for the training and 20% of images are used for the testing.

The features extracted from one of the deeper layers of Alex-Net named 'fc6' using the "activations" method. The output of (fc6) layer is a 4096-dimensional vector. The 'MiniBatchSize' is set to 22. The mini-batch is defined as a subset of the training data which used to assess the gradient of the loss function in addition to updating the weights[25]. To speed-up the multiclass SVM, the activations output is arranged as columns.

The system and its stages are implemented using MATLAB 2017 on a laptop with Core i7 CPU running at 2.8GHz.

The learned filters on the first layer of the used convolutional neural network (Alex-Net) are shown in Figure 6, It contains mostly edges and colors, which indicates that the filters at layer 'conv1' are edge detectors and color filters. The edge detectors are at different angles, which allows the network to construct more complex features in the later layers. Moreover, the filters learned on (fc6) layer is shown in Figure 7, This layer is towards the end of the network and learns high-level combinations of the features learned by the earlier layers.

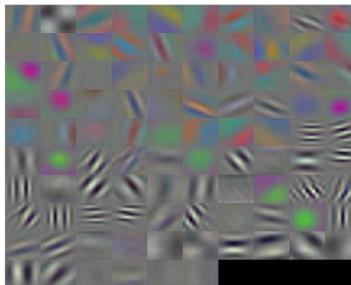


Figure 6. Filters learned on the first layer of CNN (Alex-Net) on IIT Iris Database

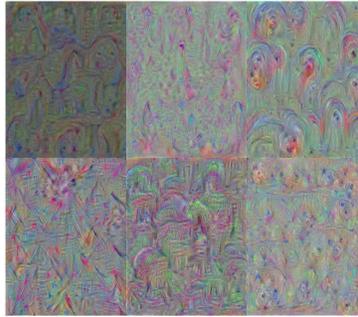


Figure 7. Filters learned on (fc6) layer of CNN (Alex-Net) on IIT Iris Database

As stated earlier, different layers encode different levels of visual content. To investigate the performance due to each layer in the used CNN (Alex-Net), the recognition accuracy is estimated after using the output from each layer as a feature vector to represent the iris. The recognition accuracy is illustrated in Figure 8 and Figure 9 when the features are extracted from the iris segmented image and from the iris normalized image respectively.

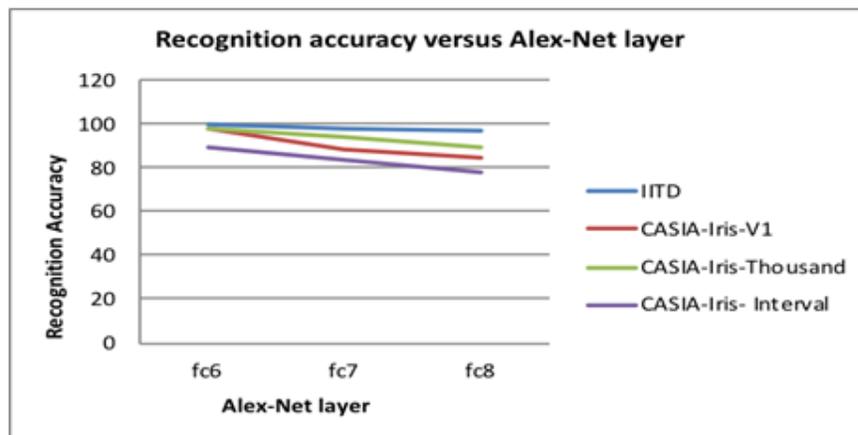


Figure 8. The recognition accuracy after segmentation stage versus different Alex-Net layer

As it can be seen from Figure 8. and Figure 9., in both cases of using the iris segmented image and the iris normalized image, the features from the (fc6) layer have the highest recognition accuracy and after that, the recognition accuracy drops. That because the higher layers of the Alex-Net model, maybe cannot distinguish much between diverse iris patterns because they capture only the abstract and high-level information, while the mid-level features in the fc6 layer have additional distinguished power for same-class recognition.

The proposed system recognition accuracy and the required time to extract the features for each iris image for the four databases are shown in Table 4. The recognition accuracy after the segmentation stage is better than the recognition accuracy after the normalization stage that because Alex-Net architecture can capture the discriminative visual features in the segmented iris image better than the normalize iris images. but the time for extracting features after the normalization stage is less than the time for extracting features after the segmentation stage.

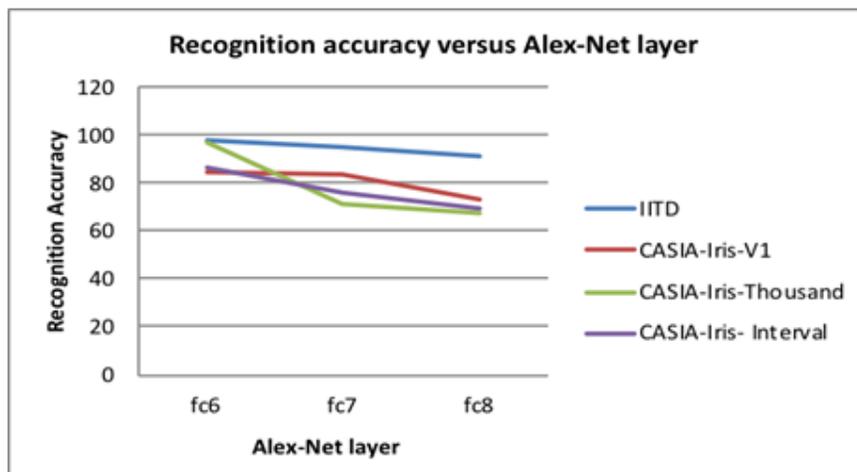


Figure 9. The recognition accuracy after normalization stage versus different Alex-Net layer

Table 4. The recognition accuracy of the adopted iris image databases.

| Database | After Segmentation | | After Normalization | |
|-------------------------|----------------------|----------|----------------------|----------|
| | Recognition Accuracy | Time (S) | Recognition Accuracy | Time (S) |
| IIT Delhi Iris Database | 100% | 0.06 | 98.33% | 0.015 |
| CASIA-Iris-V1 | 98% | 0.08 | 85% | 0.02 |
| CASIA-Iris-Thousand | 98% | 0.06 | 96.6% | 0.02 |
| CASIA-Iris-Interval | 89% | 0.09 | 86.6% | 0.02 |

The proposed system recognition accuracy for iris image after segmentation and the required time to extract features for each iris image are compared to other systems as illustrated in Table 5, the proposed iris recognition system has overall, outperformed than other feature extraction algorithms which include, Intersecting Cortical Model (ICM) network [28], circular sector and triangular DCT [29], discrete wavelet transformation (DWT) [30], Radon transform and gradient-based isolation [31], Discrete Wavelet Trans Intersecting Cortical Model (ICM) network form (DWT), Discrete Cosine Transform (DCT) [32], scattering transform and textural features [6] and the feature extraction using pre-trained VGG-Net [5]. Also, the proposed system feature extraction for each image takes less time than previous algorithms.

6. CONCLUSIONS

This paper evaluated the extracted learned features from a pre-trained Convolutional Neural Network (Alex-Net) followed by multi-class SVM algorithm to perform iris recognition. The iris is segmented using circular Hough transform and normalized using rubber sheet model. The segmented and normalized image is fed as an input to the CNN (Alex-Net). The proposed system is tested on public datasets (IITD iris databases, CASIA-Iris-V1, CASIA-Iris-thousand, and CASIA-Iris- Interval), and a high accuracy rate is achieved. The results showed that the recognition accuracy when extracting features from the segmented image is higher than when extracting features from the normalized image.

In the future, we will evaluate the performance of the proposed algorithm using the different pre-trained model in more iris datasets with other biometric recognition problems.

Table 5. Comparison Between the Performance of The Proposed Iris Recognition Scheme and The Other Algorithms

| Reference# (Year) | Feature Extraction | Database | Recognition Accuracy | Time (S) |
|-----------------------------------|--|--------------------------------|----------------------|---------------|
| [28] (2008) | Intersecting Cortical Model (ICM) network | CASIA-Iris-V1 | 97.74% | Not available |
| [29] (2012) | circular sector and triangular DCT | IIT Delhi Iris Database | 97.12% | Not available |
| [30] (2013) | discrete wavelet transformation (DWT) | IIT Delhi Iris Database | 99.5 | Not available |
| [31] (2014) | Radon transform and gradient-based isolation | IIT Delhi Iris Database | 95.93% | 0.10 |
| | | CASIA-Iris-Interval | 84.17% | 0.44 |
| [32] (2015) | Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) | IIT Delhi Iris Database | 97.81% | 93.24 |
| [6] (2015) | Texture+ Scattering Features | IIT Delhi Iris Database | 99.2% | Not available |
| [5] (2016) | pre-trained VGG-Net | IIT Delhi Iris Database | 99% | Not available |
| | | CASIA-Iris-Thousand | 90% | |
| The Proposed scheme (2018) | pre-trained Alex-Net | IIT Delhi Iris Database | 100% | 0.06 |
| | | CASIA-Iris-V1 | 98.3% | 0.08 |
| | | CASIA-Iris-Thousand | 98% | 0.06 |
| | | CASIA-Iris-Interval | 89% | 0.09 |

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