An Iris Recognition System Using Deep convolutional Neural Network

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Abstract. Machine learning rises in varied areas of computer science. A deep conventional neural network is powerful visual models of machine learning. We tend to present robustness and effective structure for the iris recognition system. The image first pass through these stages: enhancing the image quality, determine the iris and pupil center and radius for iris segmentation, converting the image from the Cartesian coordinates to the polar coordinates to reduce the time of processing. The proposed system is named IRISNet that extracting the feature and classifying them automatically without any domain knowledge. The architecture of IRISNet consists of Convolutional Neural Network layers for extract feature and Softmax layer to classify these features into N classes, for training CNN the backpropagation algorithm and Adam optimization method are used for updating the weights and learning rate, respectively. The performance of the proposed system was evaluated using IITD V1 iris database. The results obtained from the proposed system outperform supervised classification model (SVM, KNN, DT, and NB). The identification rate 97.32% and 96.43% for original and normalized images respectively. The recognition time per person is less than one second.

Keywords: Deep learning; Iris Convolutional neural network; deep Iris recognition.

1. INTRODUCTION
Recently, technology has become an important and fundamental part of every individual. Traditional methods are not efficient. Most of these methods are susceptible to lose, Hacking, forget or damage such as credit cards, identification cards, and even passports (Prabhakar et al., 2004). This has led to the need to work more secure and reliable methods of these traditional methods where a person can put documents and money and difficult to access by any person or Hacking. Biometric can achieve this security for recognition and authentication, where each person has feature and characteristics couldn't own by two people, e.g., the lines found in a fingerprint, the sound signal (voice), the dimensions, and measurements of facial, the characteristics and feature of the iris, etc.(Cireşan et al., 2012).

Building a biometric system depends on a set of stages. The first stage depends on the image or video that contains feature that wants to recognize, for example, the eye or the face, then preprocess of the input image because sometimes the lens of the camera contains dust or the movement of the person when capturing the image or rotate and other problems, the next step find the feature such iris or face and convert these feature to template to store them on the database and compared with other person templates to recognize identity. To Build a strong system with good specifications and ensure speed and
accuracy depends on the methods used to feature extraction, classification and then recognize feature. Deep learning can achieve these standards many research has begun using deep learning in their methods (El-Rahiem et al., 2019), machine learning enables the system to automatically extract features, classify and detect patterns without explicitly programming them. Some of patterns recognition based on deep learning method is object detection (Ren et al., 2015), and face recognition (Wen et al., 2016). Deep learning was also used in the iris recognition system where many researchers used deep learning to solve the problem of segmentation, classification, and recognition, e.g., of segmentation (Rot et al., 2018 & Gangwar & Joshi, 2016), recognition, and classification (Cireşan et al., 2012). In this proposed paper, we will investigate an Iris recognition system depends on extracts the iris from the other parts of the eye like an eyelid, eyelashes, and sclera by using handcrafted methods and then extract features by using a deep convolutional neural network IRISNET.

2. DEEP CONVOLUTIONAL NEURAL NETWORK BACKGROUND

Also is known ConvNets, DCNN or CNNs. It usually used in image recognition or classification. This technique developed in the 1980s - 1990s but it revived in 2012 and begins using in most of the fields of computer vision and has begun to grow fast. DCNN is not just contains many hidden layers, but it is simulates the brain by identifying images. It has the ability to extract features instead of manually designing them by using numbers of locally connected layers that have the ability to automatic feature recognition, and a number of fully connected layers for classification (Kim, 2017). Extraction feature of neural networks consists of special types of neural networks. Determined by training and updating weights. DCNN converting the manual methods for extracting features into automatic process. DCNN consists of a set of layers each layer performs a specific function (Moons et al., 2018). The most common layers in terms of structure and function will be illustrated:

The convolutional layer (conv): is made from sets of learnable filters, each filter consists of a set of weights. The weight values were selected randomly and learned via backpropagation algorithm. the learned weight is the filter that convolved through the whole image where the result is the feature map (Gad, 2018). The features map determines the unique features in the original input image. The feature map is computed according to the equation:

\[ Z^s = f \left( \sum_{t=1}^{q} W_t^s \ast X^t + b_s \right) \]  \hspace{1cm} (1)

Where: * is a two-dimensional discrete convolution operator, b is a trainable bias parameter, and f is the activation function (Minaee et al., 2016), The Rectified Linear function (ReLU) is the common activation function used with DCNN.

Pooling layer (pool): Max-pooling layers (Nagi et al., 2011) compute the maximum value of a local patch (2 × 2 or 3 × 3) of the convolutional feature map output units. So it reduces the dimension of the feature representation. The main advantage of using pooling layer is to reduce memory requirements and the computational time by removing the features that have not important in CNN. The max pooling operation can be represented:

\[ y_{j,k} = \max_{0 \leq m,n < s} (x^i_{j.s+m,k.s+n}) \] \hspace{1cm} (2)

Where \( y_{(j,k)i} \) stands for a neuron that is found in the ith output activation map, and it is calculated across an \((s \times s)\) non-overlapped local area in the ith input map \( x_{(j,k)i} \).

Fully connected layer (FC): The output of last pooling or convolutional layers is input to fully connected layers (FC) same a traditional neural network. Softmax layer: The last layer of a DCNN that it uses to classify the extracted feature from previous layers into N classes. It is often outputs the class membership probabilities turns numbers from logits into probabilities that sum to one. The softmax operation can be calculated:
\[
\text{Softmax} \left( y_i \right) = \frac{e^{y_i}}{\sum_j e^{y_j}}
\]  

3. RELATED WORK

In 1936, Frank Birch, an ophthalmologist, suggested the first idea of using an iris to identify people. The concept of Birch was adopted by American ophthalmologist Aran Safir and Leonard Flum say that iris characteristic for each person different from another; their clinical ideas couldn't be developed. The first system identifies persons by the iris was introduced by Dougman he introduced a powerful system with high accuracy and speed, where it was applied to more than one database. Use the Gabor filter to extract the iris characteristics, in the matching phase use the Hamming distance (Daugman, 2009).

Bilos use Zero crossing Wavelet Transform (WT) to extract iris properties. Before that, the iris image normalized to have the same number of data points then extract the features.

for matching, dissimilarity function was used(Boles & Boashash, 1998). Homayon use ANN for recognize the iris and LAMASTER neural network used to split the database(Cireşan et al., 2012). Deep learning has proved its usefulness in classification, where it has been used in many applications where it is classified without human intervention. The advantage of Deep conventional neural network (DCNN) Able to learn features in a similar way to a human mind while traditional neural network couldn't learn feature. there are many deep conventional neural network (DCNN) method iris like Google Net(Szegedy et al., 2015), AlexNet(Krizhevsky et al., 2012), ResNet (Szegedy et al., 2017), VGGNet(Simonyan & Zisserman, 2014), while the second DeepIrisNet-B replace the final two blocks with inception modules(Szegedy et al., 2015).

This paper proposed an iris recognition system based on deep conventional neural network, namely IRISNet. This study is set out in different sections. Sect. 3, describes the proposed Iris recognition system while Sect. 4, presents experimental result and evaluations of the proposed method and finally Sect. 5. Contains the conclusion and future work.

4. IRIS RECOGNITION SYSTEM

Name of system is going from combine many methods or sub methods in one frame to make iris recognition and consist of many methods that are:

1. Input device for images include the iris (not isolation from pupil).
2. Pupil/Iris detection.
3. Features extraction and classification
4. Matching.

The proposed iris recognition system consists of these steps: first the input image preprocessing to detect the iris from another part of the eye and then extract the feature and classify them.

5. IMAGE PREPROCESSING

The preprocessing aims to locate valid iris texture regions from a noisy background. The main reason of the iris segmentation is to remove the insignificant parts of the input eye image such as eyelid or eyelashes and only take the iris to be considered as an input to the next step feature extraction(Rot et al., 2018). To localize the iris and the pupil, we apply these steps: enhance the image by using histogram equalization(Manvi & Singh, 2012), and median filter(Gonzalez & Woods, 2007). Then determine the inner boundary (iris-pupil) by use gamma correction and blurring the image using disk filter after that convert the image into binary using global thresholding Otsu method (Otsu, 1979) and apply CHT (Johar & Kaushik, 2015) to detect the center and the radius of the iris. To detect the outer boundary (iris-sclera) canny edge detection is used to detecting the edge from preprocessing image and use CHT to extract the radius of iris Figure 1. shows the result of iris detection. After extract the iris boundaries Dougman rubber sheet model (Johar & Kaushik, 2015) used to convert iris from polar coordinate to rectangle coordinate, see Figure 2.
6. PROPOSED IRISNet ARCHITECTURE

Here, we will provide an effective model for the iris feature extraction and classification. The structure of the proposed model is composed from 4 Convolution layers, 6 activation Relu layers, 3 Pooling layers and 2 fully connected layers to classify and extracted features from image automatically without any domain knowledge. IRISNet contain 18 layers as shown in a Figure 3. start with convolution layer, followed by Rule, Pooling, and fully-connected (FC) layers and end with Softmax layer. For removing overfitting in the fully connected (FC) layers, 2 dropout layers used at the end of each fully connected layer are used. It prevents all neurons from simultaneously updating weights. This layer prevent all neurons from meeting the same target. The database split into two separate parts designed (D set) and tested (T set). The design part has also been separated into two parts training and validation.

The aim of the split design data to training and validation is to reserves a part of the design data and uses it to monitor the performance. After complete of the training the images in the designed part (D set), the tested images (T set) classified based on training images in the (D set). At the beginning of training CNN, the weights are randomly selected. Obviously, it does not give good results. The main goal of training in deep learning is to begin with a bad performance network, and finish with a high-resolution neural network. The loss function should be reduced as possible at the end of the training. Learning rate is used to update the weight. There are many algorithms used to optimize the loss functions. These algorithms can gradient-based or not. One of the simplest gradient-based algorithms is called Adam (Kingma & Ba, 2014), the training procedure is performed using the backpropagation algorithm (Gad, 2018), and Adam for updating the weight. The weight update with mini batch 20, where every set in the training data are split to mini batches, for each mini batch the errors are calculated in the Softmax layer and get backpropagation to the lower layers. The number of epoch is determining manually and the number of iteration per epoch is determining according this equation:

$$\text{num}_{\text{iterations}} = \frac{\text{number of training Image Label}}{\text{mini batch size}}$$ (4)
At the end of each epoch iteration, the validation set was used to measure the accuracy of the current configuration. Finally, after the training procedure is finished, the testing set is used to measure the efficiency of the network. Figure 4 illustrate the trained convolutional layer. Detailed steps for the proposed model are illustrated by the following algorithm:

**Algorithm 1** Implement the major steps of proposed IRISNet feature extraction and classification model.

**Require:** Data-base images \( \text{Img} = \{ I_1, I_2, I_3, \ldots, I_n \} \) design and test images should be \( I \notin G \)

**Training step:**
1. Split \( \text{Img} \) into two parts (design set, test set).
2. Split design set into two parts (Training (Tr set), Validation (Val set)).
3. Train (IRISNet, Tr set, Val set).
4. Finish training when meeting the acceptance performance and criteria.
5. Return: Train IRISNet.

**Testing step:**
1. Evaluation IRISNet by use metrics on Table 2.
2. Extract the features \( \text{testf} \) for \( I \) at FC7.
3. Training classifiers mentioned in table 2 Using \( \text{testf} \).
4. Evaluate \( \text{testf} \) by using the performance evaluation mentioned in Table 2.
5. **End.**

**Figure 3** Proposed IRISNet layers.
7. DATABASE
The database used is the base of IIT Delhi version 0.1. Where the database consists of images for each person, 5 rights and 5 left except persons 1-13, 27, 55 and 65 left eye images only. The age of the persons between 14-15 years. They are 167 males and 48 females only. The images bitmap format and taken in a closed environment for students and staff the size of each image 320 x 240 pixel. A database sample in Figure 5.

![Figure 4](image)

**Figure 4** Visualize trained convolutional Layers of IITD Dataset

8. EVALUATION METRICS RUSLTES
The evaluation of the proposed IRISNet using IITD iris dataset (Simonyan & Zisserman, 2014), to calculate the accuracy of classification that is extracted the features from the test and training data in the layers 17 'Softmax ', then classify these feature at FC2 based on another classification model (SVM, KNN, NB, DT)(Manvi & Singh, 2012). All models were evaluated by use common performance evaluation (Sensitivity, Accuracy, Specificity, Precision, Recall, G mean and F Measure). For recognition performance evaluation two experience have been evaluated, first experience exp1 was on the database take the whole image without segmented the iris, while exp2 applied to the database of the image after normalized the iris. The database was split into 80% design and 20%test (i.e. each person has 10 images 8 images for design and 2 images for testing). All the design images in this trial are 1792 images and 448 images for testing. The design image is split into 80% training and 20% validation i.e. 1344 images for training (each person 6 images) and 448 images for validation (each person 2 images) the results show that the recognition rate is 95.98% for normalized iris images and 97.32% for iris images without segmentation.

![Figure 6 and Figure 7](image)

**Figure 6.** and **Figure 7.** illustrate the accuracy and loss rate for iris image without segmentation (exp1) and normalized (exp2), respectively. The training time for 20 epochs is (00:16:05) minutes for the iris image without segmentation and (00:14:26) minutes for the normalized iris image. Table 2. and Table 3. show the estimated performance for the behavior of the IRISNet model. Training and validation step
check accuracy is satisfying. The evaluation performance of tow experiment, shown in Table 1. and Table 2., respectively. In the case of exp1, the IRISNet achieved the best performance when Compare with other classification methods (SVM, KNN, NB, DT) the accuracy 0.9643, while exp2 the performance was0.9732 see Table2. Figure 9. comparison between the two experiences.

Table 1 Performance evaluation of the IRISNet without segmentation iris image.

| Classifier      | Accuracy | Sensitivity | Specificity | Precision | Recall | G-Mean | F1 Measure |
|-----------------|----------|-------------|-------------|-----------|--------|--------|------------|
| Soft-Max        | 0.9732   | 1.0000      | 0.9709      | 0.1333    | 1.0000 | 0.9853 | 0.2353     |
| SVM             | 0.9107   | 1.0000      | 0.9103      | 0.0476    | 1.0000 | 0.9541 | 0.0909     |
| KNN, (k=2)      | 0.9353   | 1.0000      | 0.9350      | 0.0645    | 1.0000 | 0.9669 | 0.1212     |
| Naive Bayesian  | 0.9196   | 1.0000      | 0.9193      | 0.0526    | 1.0000 | 0.9588 | 0.1000     |
| Decision Tree   | 0.4356   | 1.0000      | 0.4300      | 0.0172    | 1.0000 | 0.6557 | 0.0339     |

Table 2 Performance evaluation of the IRISNet with normalized iris image.

| Classifier      | Accuracy | Sensitivity | Specificity | Precision | Recall | G-Mean | F1 Measure |
|-----------------|----------|-------------|-------------|-----------|--------|--------|------------|
| Soft-Max        | 0.9643   | 1.0000      | 0.9643      | 0.1111    | 1.0000 | 0.9819 | 0.2000     |
| SVM             | 0.9241   | 1.0000      | 0.9238      | 0.0556    | 1.0000 | 0.9611 | 0.1053     |
| KNN, (k=2)      | 0.9308   | 1.0000      | 0.9305      | 0.0606    | 1.0000 | 0.9646 | 0.1143     |
| Naive Bayesian  | 0.9152   | 1.0000      | 0.9148      | 0.0500    | 1.0000 | 0.9565 | 0.0952     |
| Decision Tree   | 0.3705   | 0.5000      | 0.3700      | 0.0035    | 0.5000 | 0.4301 | 0.0070     |

Figure 5: Accuracy and loss rate of IRISNet classification without segmentation iris image.
We also evaluate the performance of the proposed IRISNet using two pre-trained models AlexNet and VGGNet-16, which are pre-trained on iris image dataset. Table 3. shows the accuracy of the two models. Figure 9. shows samples of classification image trained in IRISNet.

**Table 3** Comparison between IRISNet and another pre-trained models

| Pertained CNN   | Recognition Accuracy | Training Time   |
|-----------------|----------------------|-----------------|
| IRISNet         | 96.43%               | 01:15:30        |
| AlexNet         | 95.09%               | 01:08:50        |
| VGGNet-16       | 94.42                | 24:01:5         |
9. CONCLUSION
A deep convolutional neural network (DCNN), a class of artificial intelligence that becomes controlling in a variety of domains. Deep learning automatically learning features. Thus provide a good understanding for data without depending on any handcrafted features extraction. On this paper we present an effective iris image feature extraction and classification network. The proposed approach preprocessing the image to extract the iris then extract feature by adapted Convolution layers, Pooling layers, Relu layers, Dropout layers, Fully Connected layers, and Softmax layers as part of DCNN for classify IITD iris images. The trained IRISNet the evolution of the performance is done by a set of evaluation metrics using DCNN for extract the features of the iris image that input to the input layer. Train extracted feature on a set of classifiers model (implement on Section. 4.2), training features (training set) was used, and then the classifier was measure by using a testing feature (test set). Table 2 and Table 3 show the IRISNet performance evaluation. Evaluate the proposed system with initial number of epochs in 50 we observed that the learning process was stable in affixed range. For future work use of IRISNet on another iris databases.

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