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Iris Recognition System Based On Efficient Model For CNN Features Extraction And SVM Classifier

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Abstract

Iris recognition relied on iris features to verify and identify a person's identification. The iris texture provides a number of advantages, including long-term stability, ease of use, and excellent recognition accuracy. The most critical stage in the iris recognition system is extracting effective features. The majority of earlier iris recognition feature extraction methods used hand-crafted features. The Convolutional Neural Network (CNN) has recently been shown to be effective in most recognition problems. As a result, using CNN-extracted features in an iris identification system attracts our attention. In this paper, we will present the details of building an efficient system for iris recognition based on a number of design stages. Firstly, the pre-processing techniques, segmentation by using Circular Hough Transform (CHT), and Normalization by using Duagman Rubber-Sheet Model are applied to the image of the human eye to determine the region of the iris. Secondly, the new structure of CNN architecture is proposed to extract features from the normalized iris region. Finally, the SVM classifier is applied to classify the images in the CASIA- Iris Dataset V1. The hyper-parameters chosen and the deep networks and optimizers tuned to affect the performance of our proposed system. For the dataset utilized in the experiments, the suggested CNN architecture achieves 99.07% accuracy, outperforming current approaches.

Keywords: Iris Recognition, Features Extraction, Convolutional Neural Networks (CNN), SVM Classifier.

1. Introduction

Iris recognition refers to recognizing persons by the automated method based on iris patterns of them. It is one of the most promising biometric identification methods in use today, and it is widely employed in numerous fields. In big databases, iris recognition algorithms have high matching efficiency. Due to advantages such as autonomous learning, high accuracy, and excellent ability of generalization, various deep learning algorithms have recently been applied in biometric recognition[1][2]. Deep learning techniques have recently emerged to be highly effective in automating and manipulating the process of extracting and learning features from images, hence obviating the need for the time-consuming task of feature engineering [3][4]. Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that is used to process images and videos. CNN networks have surpassed many traditional hand-crafted methodologies because of their ability to learn image feature representations by using repeating blocks of neurons (Convolutional layers) that are applied on the images hierarchically[2].

CNN networks are efficient Deep Neural Networks (DNNs) that are frequently used in pattern identification and image processing. CNN networks have the capacity to extract distinguishing features from input images without the need for pre-processing. Furthermore, when compared to other DNNs, CNN has a number of advantages, including fast convergence, a simpler design, adaptability, and fewer free parameters. Furthermore, CNN is unaffected by image deformations like translation, rotation, and scaling. [5][6]. In terms of translation, small rotation, and deformation, a good feature should have some degree of invariance. [7][8]. SVM is a supervised machine learning technique that may be used for both classification and regression. Each data item in SVM is represented as a point in n-dimensional space, with the number of dimensions equal to the number of features to be classified. By determining the hyper-plane that distinguishes between number of groups of scattered data points, the categorization is accomplished [9].

2. Review of Related Studies

In 1987, the first automatic iris recognition system was developed. One of the most influential algorithms of iris recognition proposed by the Daugman. Where he was able to identify the boundary of the iris and pupil was originally recognized by the integro-differential operator and normalized by Daugman's rubber-sheet model in his research. By using the Gabor phase-quadrant feature descriptor, the extracted iris was turned into a sequence of encoding (IrisCode). Finally, between IrisCode, the hamming distance was calculated for the identification or verification step, and the recognition result was obtained. In today's iris recognition systems, Daugman's algorithm and methodology are still commonly used [10]. Later, numerous iris feature extraction approaches that used several features extraction methods. Asaad Noori Hashim, et al. suggested iris recognition system based on the fusion of scale-invariant feature transforms (SIFT) along with local binary patterns to extraction of features. A number of steps have been taken. To begin, any form of image was turned to grayscale. The circular Hough transform was used to localize the iris in the second step. Finally, Daugman's rubber sheet model was used for iris normalization to convert the polar value to Cartesian, then using the method of enhancement the normalized image as the histogram equalization. Finally, the SIFT and local binary pattern were used to extract the features. For feature extraction, some sigma and threshold values were employed, which resulted in the maximum recognition rate. The city block distance was used to perform the matching. The CASIA v4 iris identification system was constructed using iris scans from 30 different people. Each person has 20 left and right captures, for a total of 600 images. Among thirty respondents, the major findings revealed that recognition rates for left and right eyes 98.67% and 96.66% respectively. [11]. S.Sujana, et al. proposed an recognition system for iris based on three steps: first,pre-processing techniques that includes the segmentation (using: Circular Hough transform) and perform the normalization by Daugman's process. Second, the features extracted by using a proposed system (by: CNN Model) that is trained for this purpose. The SoftMax classifier is then used to categorize the iris data into one of 224 classes from the IITD iris dataset, as well as 108 classes from the CASIA V1 iris dataset. The choice of hyper parameters, tuning of the deep networks, and optimizers influence the performance of the proposed system. By reaching accuracies of 98 % and 95.4% respectively[12].

Recently, deep learning-based iris recognition approaches have been increasingly studied. Tianming zhao, et al**.** proposed system by using deep learning techniques for iris recognition. In this work, the capsule network design is used in the deep learning method. To adapt this technology to iris identification, the architecture of the network is updated, and they give a modified routing algorithm based on dynamic routing between two capsule layers. Even when the number of samples is restricted, migration learning allows the deep learning method to be used. As a result, three cutting-edge pre-trained models are introduced: VGG16, InceptionV3, and ResNet50.

According to the number of primary constituent blocks in the three networks, they classify them into a series of subnetwork architectures. Instead of a single convolutional layer in the capsule network, they are used as the convolutional component to extract primary features. The outcomes of this study's experiments are influenced by the various networks structure [1]. Kranthi Kumar K, et al. proposed a biometric system based on recognition of iris. Among other biometric qualities, the iris is the most secure and distinctive. They proposed a modified Hough Transform and used the Mini-VGG Net model without its weights to train the network to acquire the best features in this paper. They did the categorization using Neural Networks and obtained Accuracy, Precision, and Recall of 98 percent, 0.99, and 0.99, respectively. The CASIA Version-1 was used to conduct the experiments, which included 756 iris samples in 108 folders, each with 7 samples measuring 280×320 pixels. [13]. Jie Sun, Shipeng Zhao, et al. presented a study based on deep learning that suggests open-set recognizing the iris of the eye. In the methodThe retrieved iris features are clustered in the feature center of each type of iris image after training the deep network. The authors next construct an open-class features outlier network (OCFON) with distance features, which maps the deep network's extracted features to a new feature space and categorizes them. Finally, a SoftMax probability threshold is used to determine the unknown class samples. The authors tested their findings on an open iris dataset created by combining the CASIA-Iris-Twins and CASIA-Iris-Lamp iris datasets. The results reveal that the proposed method performs well in open-set iris identification, can efficiently identify iris samples of unknown classes, and has no effect on the capacity to recognize known classes of iris samples [14].

The goal of this paper is to develop a deep learning approach for features extraction with strong robustness to various iris contaminations. To meet this goal and overcome the limitations mentioned above, we construct a new CNN model for effcient features extraction. The extracted features are used to train a multi class SVM classifier to get the person identity.

2. Proposed Iris Recognition System

The proposed system includes three steps: **Image pre-processing**, **CNN Model for Iris Features Extraction**, and **SVM Classification**. The image pre-processing module includes iris segmentation and normalization of the iris images. In the feature extraction stage, a deep network is designed. The network design includes building the CNN model consisting from several layers for training the iris images and extracts the features. Finally, the classification step includes using SVM as the classification module to classify the extracted CNN feature vector. Figure (1) shows the structure of the proposed system.

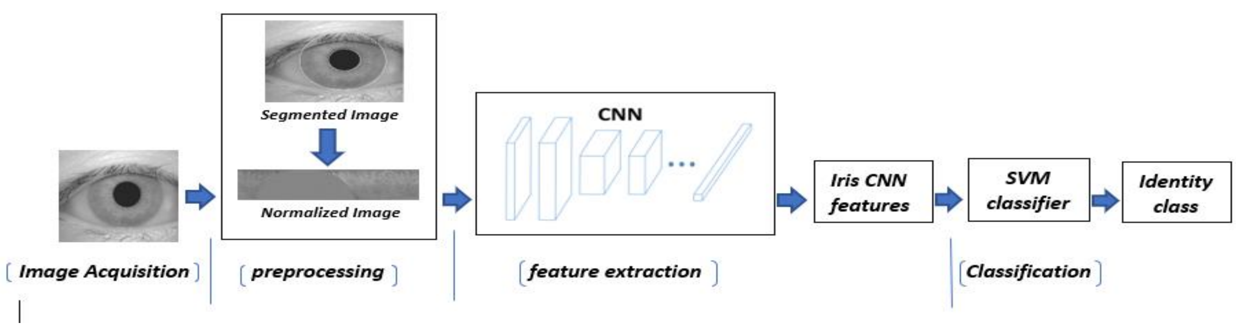

Figure (1): The framework for Iris Recognition System

3.1 Image Pre-processing

Eye images, including the iris, which are taken using certain cameras and unrestricted environments that contain a number of obstacles that affect the identification of the iris such as clogged eyelids, overlapping eyelashes with the iris, light reflection on the eye or certain eye diseases. Therefore, a preliminary treatment is applied to the eye image to determine the region of the iris so that it can be identified more accurately.

3.1.1 Iris Segmentation

Iris segmentation is the process of separating the iris texture from other visual features including eyelids, lashes, highlights, and/or shadows. The segmentation module also creates a binary mask that shows which pixels in the image belong to the iris texture. [15]. The iris region's is first determined by extracting two circular contours corresponding to the iris region's inner and outer limits. [2]. One of the circle detectors that commonly used in iris detection step is the Circular Hough Transform (CHT) that used in this system for segment the iris region and can be explained mathematically as,

$$(x-a)^2+(y-b)^2=r^2 \quad \dots (1)$$

Where the radius is denoted by r and the iris center represented by (a, b) and the circle coordinates by (x, y). The result for this step is shown in Figure (2), and the accuracy for this method equivalent 99.16 on the CASIA -Iris Dataset.

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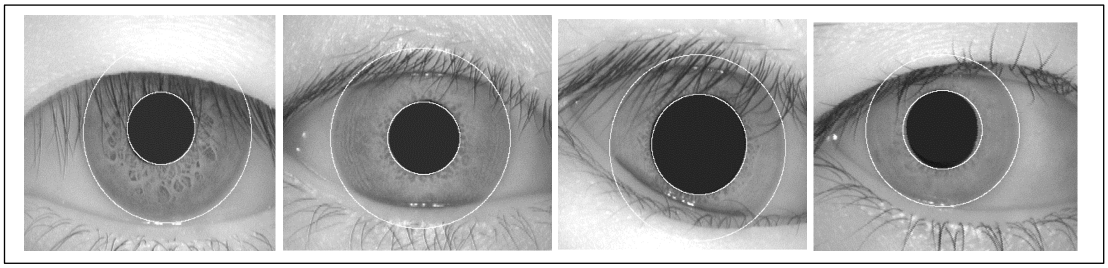

Figure (2): Examples of Iris Segmented samples

3.1.2 Iris Normalization

In this step, the segmented iris region is converted into a fixed-dimensional rectangular region so that it is easy to work with and extract features. To do this process, Daugman proposed usage of a Rubber-Sheet Model. This method realized on re-mapping the iris region, I (x, y), from Cartesian coordinates (x, y) to polar coordinates (r, θ)which is dimensionless, this can be explain by equation[2],

$$I\big(x(r,\theta),y(r,\theta)\big)\rightarrow I(r,\theta) \quad \dots (2)$$

where r is in the interval [0,1], and the angle θ in the range of [0,2π]. x (r, θ) and y (r, θ) are defined as the linear combination of both pupillary $(x_p(\theta),y_p(\theta))$ limbic boundary points $(x_s(\theta),y_s(\theta))$ as,

$$x(r,\theta)=(1-r)x_p(\theta)+rx_s(\theta) \quad \dots (3)$$

$$y(r,\theta)=(1-r)y_p(\theta)+ry_s(\theta) \quad \dots (4)$$

Figure(3) shows the pre-processing step in iris recognition system.

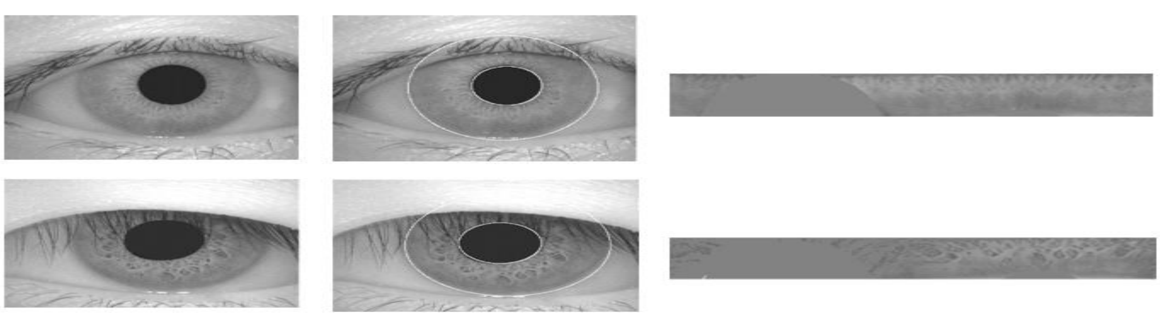

Figure (3) Pre-processing steps (a) Original Image (b) Segmented Image (c) Normalized Image

3.2 CNN Model for Iris Features Extraction

In this work, the iris features are extracted using CNN Algorithm. Where a CNN model consisting of several layers (convolutional, pooling, and fully connected layers) was designed and trained to get these features with good accuracy. Then the feature vectors that extracted by the CNN network are fed to the classification module. We use a simple multi-class Support Vector Machine (SVM) because this classifier is characterized by its popularity in addition to its high efficiency in classifying images. For each layer, there is batch normalization. This is a normalization method that is used between the layers of a Neural Network rather than in the raw data. Instead of using the entire data set, it is done in mini-batches. Its purpose is to facilitate learning by speeding up training and utilizing higher learning rates.

The size of input image and Training methodology include tuning of hyper-parameters, optimizer utilized, and schedulers of Learning rate to determine the ideal CNN configuration in the recommended methodology parameters that have a big impact on the CNN performance.

3.2.1.Input Image Size

The data image size is one of the key factors in the CNN that has a significant impact on the speed and accuracy of the neural network. The size of the input image in this project is (64x512). The images are from CASIA V1.0. Each CASIA-V1 file contains 756 iris images from 108 eyes and is saved in BMP format with a resolution of 320 × 280 pixels. Seven images for each eye are taken in two sessions using the self-developed CASIA close-up iris camera technology.

3.2.2 Training Methodology

In this work, the remaining 15% of unseen samples are used for testing, with 70% of samples for training that randomly chosen and 15% of samples selected for validation using training data. Validation data is gathered to determine the network's ability to create and keep weights that operate best with the least amount of validation error. One of the important elements of training methods is determining the appropriate CNN network design. Hyper-parameters, such as the number of layers used in the network and the number of nodes in hidden layers, as well as factors that influence on the training of the network, are variables that control on the architecture of the network or topology (E.g.: Learning Rate, number of epochs). Hyper parameters are set up before to training (before optimizing the weights and bias) Table (1) presents the structure of the proposed CNN architecture.

Table (1): Proposed CNN architecture

Layer Type	Activations	Filter size, No. of Stride, Padding	Number of learnable weights
Input Image	64×512×1 (Height ×Width× Channel)	----	----
Convolutional Layer1	64×512×16	(3×3), 3,1	160
Max Pooling1	32×256×16	(2×2), 2	0
Convolutional Layer2	32×256×32	(3×3), 3,1	4640
Max Pooling2	16×128×32	(2×2), 2	0
Convolutional Layer3	16×128×64	(3×3), 3,1	18496

Max Pooling3	8×64×64	(2×2),2	0
Convolutional Layer4	6×62×64	(5×5),5,4	102464
Fully Connected Layer	1×1×108	----	2571372

As shown in the table (1) this model includes four sets of:

1- Convolutional, RelU, and a Batch Normalization layers after the activations.
2- Max pooling layers.
3- Fully connected layer (Dance layer).

In addition, using SGDM (Stochastic Gradient Decent Momentum) optimizer with a learning rate = 0.01 as initial value and momentum = 0.9. Learning rate schedulers are employed to reduce overfitting and improve classification accuracy. In addition to the important parameters improve the accuracy of the network is also the number of epochs, in this model the number of epochs is 50.

3.3 SVM Classification

After feature extraction, the classifier is used to discover the associated label for each test image. Support Vector Machine, Softmax Regression, and Neural Networks are examples of classifiers that can be used for this purpose [16]. Support Vector Machine (SVM) is a supervised machine-learning algorithm used in classification, regression and anomaly detection tasks. It has high performance in high dimensions spaces with reasonable time. The SVM draw the boundaries between the classes with maximum width possible. By considering non-linear separation lines, these separation lines (i.e., boundaries between classes) are drawn during the training time. The new instances are dropped based on their values between these boundaries. This will assign the class of this new instance.

Algorithm (1) depicts the overall steps for (Feature extraction and classification).

Algorithm (1): Extracting and Classify features using (proposed CNN model &SVM classifier)
Input: The input images (CASIA-Iris Dataset-V1)
Output: The accuracy of recognition
Begin Step1: Load input images (Dataset of Iris). Step2: split the images into three sets: training (70% from data), validation and testing (15% for each). Step3: Load the Proposed CNN Model. Step4: Extract features by the proposed model of CNN. Step5: From the training set get the training labels. Step6: To train a multiclass SVM classifier, use the training features. Step7: Extract features from test set. Step8: Predict the label for the test set using the trained classifier. Step9: Get the test set's known labels. Step10: Tabulate the results of confusion matrix. Step11: calculate the performance measure for the confusion matrix (Precision, Recall and Accuracy).

4. System Evaluation

The class must be compared to the ground line in order to assess the efficiency of this classification model. There are a number of requirements that must be met in order for classification to be effective. The ground-truth is utilized to conduct the experiments, which are based on the dataset used. Three criteria are considered in this study: precision, recall, and accuracy.

Precision or Confidence (as called in Data Mining) shows how many Predicted Positive situations correspond to correct Real Positives.

$$\text{precision} = \frac{TP}{PP} = \frac{A}{A+B} \quad \ldots (5)$$

Where, the True Positive is denoted by TP and the total sum of Predicted Positives and True Positive is denoted by PP.

Recall (Sensitivity) is the ratio of correct anomalous measurement detections to the total number of abnormal measures. [4].

$$\text{Recall} = \frac{TP}{RP} = \frac{A}{A+C} \quad \ldots (6)$$

Accuracy is calculated as the total number of right predictions divided by the total number of valid predictions in the dataset. The highest level of accuracy is 1.0, while the lowest level is 0.0.

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N} \quad \ldots (7)$$

5. Experimental Results & Comparisons

We show the suggested system's performance analysis as well as a comparison to existing research on this dataset (CASIA-Version1), which contains 756 iris images from 108 folders with seven samples for each class. The training and validation accuracy plot and the loss function plot, of the proposed CNN for the Dataset CASIA-Iris V1 shown in figures (4) and (5). The proposed architecture accuracy for this Dataset is 98.15% in the validation phase, and 98.14 in the testing phase. The proposed CNN design is trained by using Stochastic Gradient Decent Momentum (SGDM) optimizer. And the dataset is split into 70% training, and 15% for each the validation and testing. The training phase have 50 epochs. And the batch size is 32.

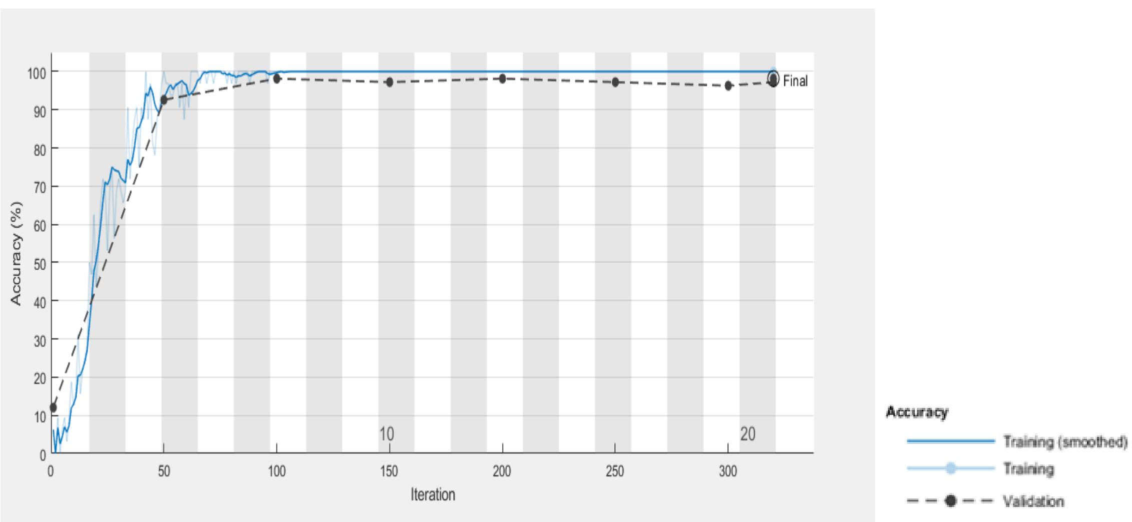

Figure (4): the training and validation accuracy over the iterations

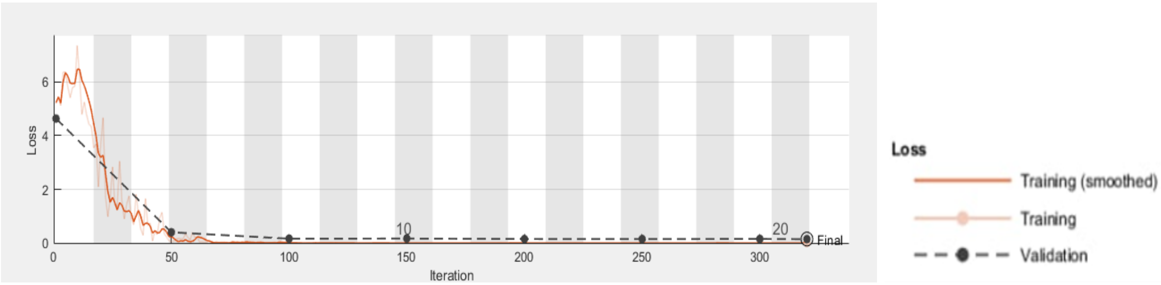

Figure (5): Loss Function over the iteration

One of the most critical tasks in many object identification systems is extracting good features and visual descriptors. As a result, many academics have concentrated their efforts on developing useful features that can be applied to a wide range of object detection and image classification applications.[7]. Figure (6) include some features that extract from the proposed CNN Model.

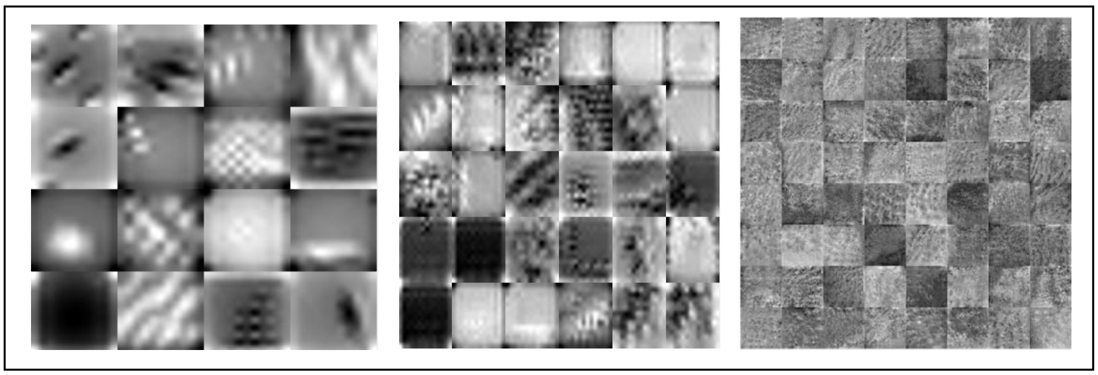

Figure (6): Examples of the output of features extracted step by CNN layers

Since the confusion matrix is used to evaluate the classification algorithm, it was used here to evaluate the classification system that used SVM classifier as mentioned earlier. Performance measures were also extracted from this matrix, which will explain in Table (2).

Table (2): The results obtained from the Confusion Matrix

Dataset (CASIA- Iris Version 1)		
Precision	Recall	Accuracy
99.07	98.61	99.07

Table (3) shows the comparison of the classification accuracy of the proposed model with other state-of-the-art approaches.

Table (3): Comparison the Proposed Method with the previous Methods

Methods	No. of Samples	Accuracy (%)
Manjunath M et al.[17]	70 class- 490 images	90

S.Sujana et al.[12]	108 class – 756 images	95.4
Kranthi Kumar K et al.[13]	108 class – 756 images	98
Maram.G Alaslani et al. [18]	60 class – 420 images	98
Maram.G Alaslni et al.[19]	60 class – 420 images	98.3
Proposed System	**108 class – 756 images**	**99.07**

6. Conclusion

In this work, an effective Iris Recognition System is shown which employs a deep learning technique to authenticate an individual's identification. To acquire images in unified form, the step of segmenting the iris using a Circular Hough Transform and performing the Normalization procedure using the Daugman Rubber Sheet Model is utilized. This phase provides an acceptable form of input to the feature extraction step. The features from the normalized iris picture are extracted using CNN architecture. The hyper parameters adjustment and the learning rate scheduler improve overall precision. CASIA-Iris Dataset is used and the Recall reached to 98.61 % and the Precision, Accuracy equivalent to 99.07%. These results are encouraging and surpass those found in previous research. In the future work, several datasets will be used to modify the proposed CNN model, resulting in a more accurate and efficient system for all databases.

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