An Effective CNN based Feature Extraction Approach for Iris Recognition System

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Abstract: Biometrics are playing an important role in security. Biometrics based on computer vision includes facial recognition, fingerprints, and iris to create efficient authentication systems. Iris identification is one of the best methods for providing individuals with unique authentication based on their IRIS structure. In this work, accurate iris recognition is based on pre-processing techniques, segmentation using Circular Hough transform along with canny edge detector, and normalization by daugman's process. Using Convolutional Neural Networks, the suggested system is trained to extract features of normalized input iris images. This is followed by the Softmax classifier to classify into one out of 224 classes from the IITD iris dataset along with108 classes from the CASIA V1 iris dataset. It can be concluded that the performance of our proposed system is influenced by the choice of hyper parameters and tuning of its deep networks and optimizers. By achieving 98 % and 95.4 % accuracies respectively, it outperforms current methods.

Keywords: Iris biometrics, Iris segmentation & normalization, Convolutional Neural Networks, Softmax classifier.

1. Introduction

Biometrics is related to human unique characteristics. The most promising methods for authenticating a user are biometric systems. Biometric authentication can be favoured over many conventional strategies, such as smart Cards and passwords since information is hard to steal here in biometrics. A biometric recognition device is used to recognize a person under surveillance and access control. Physiological characteristics and behavioral characteristics are commonly classified as biometric identifiers. Physiological characteristics are associated with the physical properties of the body, such as fingerprint, palm veins, DNA, facial recognition, iris, and so on [1].

The other category referred to an individual's model behaviour, such as voice, gait, etc. Biometrics offers an important protection platform in both physiological and behavioural ways. Biometrics has been fully integrated into our everyday lives. Many studies have shown that other biometrics such as the ears, fingerprint, the iris have several advantages. Iris is also approved for precise and accurate biometric systems. It is considered to be one of the correct biometric identification. Iris is the annular eye region between the white sclera and the black pupil, which makes it entirely shielded against environmental conditions [2].

The texture of the iris provides a high degree of randomness and individuality, which is very unlikely to be unique in any of the two iris patterns, either for identical twins or from a person's left and right eyes. This consistency in iris patterns is primarily due to the richness and differentiation within the iris texture features, including circles, ridges, crypts, freckles, furrows, zigzag patterns. This property makes it a reliable way of recognizing people. Also, the iris pattern remains constant until he died for an individual. This recognition approach is therefore considered safer and less vulnerable to spoofing attacks [3]. Finally, where an attempt to change its patterns is more risk of surgery, unlike fingerprint that is comparatively easier to manipulate, the most reliable biometric characteristic against fraudulent techniques and spoofing attempts by an impostor. The implementation of iris authentication systems, however, is a difficult job as it acquires eyelashes, reflections, and eyelids that may interfere with the recognition efficiency in a device. There are extensive uses of iris detection today in various protection applications, Such as restricted-area access control, Aadharcard database access, the bank, and other modern-day applications.

In every biometric device, there are two ways to use the system. The first is the enrolment mode, which allows the processed prototype to be deposited in the database. The second mode is the identification mode, in which the template is identified by comparing it, if it exists, to one of the templates stored in the database [4].

This research work consists: Section 2 describes the survey of existing techniques with their advantages and limitations. A brief explanation of the process involved in biometric systems is presented in Section 3, and the process involved in the Iris system is depicted in Section 4. The proposed system architecture is given in Section

5. Results and comparisons against existing techniques using a standard dataset are given in Section 6. Finally, the conclusion of the research work with future development is represented in Section

2. Review of Related Studies

Arora, S., & Bhatia, M. S. (2018) suggested method of iris recognition utilizes a deep learning approach to authenticate the identity of an individual. For iris localization, they used the Circular Hough transform followed by automated extraction of features using CNN from localized iris input image regions and then Softmax classifier for classification of the dataset into one out of 224 classes. They concluded from the result that the proper selection of hyper-parameters and optimization techniques affects the accuracy of their proposed system. They tuned to get an accuracy of 98 %. This network is not adjusted to more real-world datasets.

Menon, H., & Mukherjee, A. (2018) investigates the advantages of using dynamically generated features to address both identification and verification issues when Compared to hand-crafted features built on deep residual network models that have been fine-tuned. They applied a network designed for a different task to the issue of iris recognition. Finally, CNN can be used to efficiently remove certain vulnerabilities in traditional biometric systems, in addition to improving accuracy. For positive results in terms of accuracy and security, more research on the effective use of deep networks in traditional biometric applications, such as iris recognition systems, is needed.

Nguyen, K., Fookes, C., Ross, A., & Sridharan, S. (2017) from pre-trained CNN features, they have discussed the challenge of iris recognition. Their studies have shown that CNN features that were originally trained for object recognition can be used effectively for the iris recognition challenge. Pre-trained CNN features were originally trained for object recognition and can be used effectively for the iris recognition challenge. They used different pre-trained models like Alexnet, VGG net, Inception net, res net, dense net, and daugman and The highest peak recognition accuracy is achieved by DenseNet among all five CNNs. In two large iris datasets, ND-CrossSensor-2013 and CASIA-Iris-Thousand, they achieved recognition accuracy.

Zanlorensi, L. A., Luz, E., Laroca, R., Britto, A. S., Oliveira, L. S., & Menotti, D. (2018) Using deep representations on unconstrained environments, the impact of iris pre-processing was assessed for its iris recognition and their experiments showed that the models learned using non-segmented and non-normalized images produced the best results on the ResNet-50 architecture. For face recognition, To obtain deep representations, fine-tuning of two pre-trained CNN architectures were used. For both models for non-normalized iris, the suggested data augmentation approach obtained a better result.

Minaee, S., & Abdolrashidi, A. (2019) by fine-tuning a pre-trained Convolutional model on Image Net, an end-to-end deep learning architecture for iris recognition was proposed. This can learn the representation of the feature and perform recognition together and is particularly helpful for the other problems of recognition of biometrics where for each class, there are only a few labelled images available. The proposed work is applied to the IIT-Delhi Iris dataset, which achieved promising outcomes and improved on previous approaches to these datasets. They also show how to use visualization technique to locate the most important regions in the iris, the majority of which can affect the recognition results.

Umer, S., Dhara, B. C., & Chanda, B. (2015) presented an Iris recognition system based on a multi-scale morphological method for the extraction of a feature. Morphologic top-hat transform is applied to represent the iris features in the form of the sum of dissimilarity residues. Using the dichotomy method multi-class problems are changed to the two-class problem for classification. The suggested system performance is tested on four IITD, MMU1, UPOL, and UBIRIS iris databases.

Monro, D. M., Rakshit, S., & Zhang, D. (2007) has proposed A new iris coding technique based on differences in the overlapping angular patch coefficients of discrete cosine transformation (DCT) from normalized images. Munro applies his proposed model to the CASIA database's 2156 images and the bath database's 2955 images, achieving a remarkable 100% Correct Recognition Rate (CRR) and Perfect Receiver-Operating Feature (ROC) curves, with no false acceptance or rejection. The False Rejection Rate (FRR) and the False Acceptance Rate (FAR) are used for verification purpose. Furthermore, in the absence of matching failures and a low Equal Error Rate (EER), a new worst-case metric for actual device efficiency is proposed.

Zhang, W., Lu, X., Gu, Y., Liu, Y., Meng, X., & Li, J. (2019) has proposed a robust iris segmentation scheme called the FD-Unet, he initially stated that an accurate iris segmentation method would improve the overall performance of the system and U-Net (FD-Net) the best fully dilated network model convolution, as well as four new network schemes, were proposed. The proposed FD-Net model helps in extracting more global features than any other model and hence the author tests. With three different datasets, namely CASIA-Iris-Interval-v4.0, ND-IRIS-0405, and UBIRIS.v2, the proposed model achieves 97.36%, 96.74%, and 94.81% respectively.

Thomas, T., George, A., & Devi, K. I. (2016) proposed method is for less constrained imaging conditions for iris recognition and Due to image blurring, off-angle imaging, changes in illumination, specular highlights, and noise, the iris images can be degraded. Ellipse fitting through RANSAC Random Sample Consensus gave a good result compared to Hough transformed iris localization and Daugman’ssystem. The measure of similarity used for template matching is the Peak Side Lobe Ratio (PSR). The algorithm evaluated on the WVU iris database and promising results for both the iris boundaries but only for a limited number of iris images.

Al-Waisy, A. S., Qahwaji, R., Ipson, S., Al-Fahdawi, S., & Nagem, T. A. (2018) to identify the fast multimodal biometric system by establishing a deep learning-based framework by taking into account the left and right iris of the person, the fast multimodal authentication biometric system was proposed. By applying an automated and real-time iris location, CCHT is used to classify the region of the iris, which has enhanced overall accuracy. From the iris image to derive discriminatory characteristics without domain information Deep learning is proposed based on a combination of CNN and Softmax classifier and then classify it into one of M classes. They have tested the proposed approaches on three databases: CASIA-Iris- V3 Interval, IITD iris database, and SDUMLA-HMT and achieved an identification rate of 100% and less than one second of recognition time per person.

Liu, M., Zhou, Z., Shang, P., & Xu, D. (2019) presented for processing the image by fuzzifying the area outside the boundary, triangular fuzzy median smoothing filters, and Gaussian, triangular fuzzy average to improve the signal-to-noise ratios. Triangular fuzzy filters are easier to measure and faster. The improved images were used to train deep learning techniques through fuzzy operations to increases the recognition accuracy rate and speeds up the convergence process as well. To enable a deep learning framework, they suggested the F-CNN and F-Capsule for iris recognition. Overall, training on fuzzy images works better than training on raw images. It was not intended to examine the effect of various capture devices; it uses data sets obtained by the usual lens with two different sensors.

According to the results of the survey, some authors used conventional methods for feature extraction and classification, resulting in lower accuracy. In addition to that authors proposed, models work on a small dataset and do not present high accuracies with the large as well as other datasets

3. Process Involved in Biometric Systems

A biometric system consists mainly of two stages, namely the stage of enrolment and the phase of verification. The images are collected from a single biometric trait in the enrolment phase and are processed to obtain a clear image as well as to correct distortions and to obtain the region of interest for extracting features. The feature extraction module extracts the details from the pre-processed image.

The feature vector is created by extracting specific features from the image function and storing them in a database [13] Shown in Fig.1 Enrolment mode is a phase of learning to gather biometric data about whom to recognize. The query image that is to be tested is pre-processed to improve the quality of an image in the recognition phase.

Figure.1 Steps involved in enrolling a biometric trait

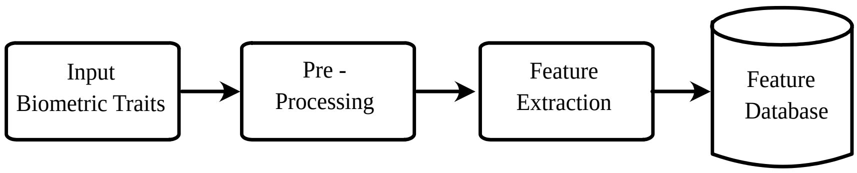
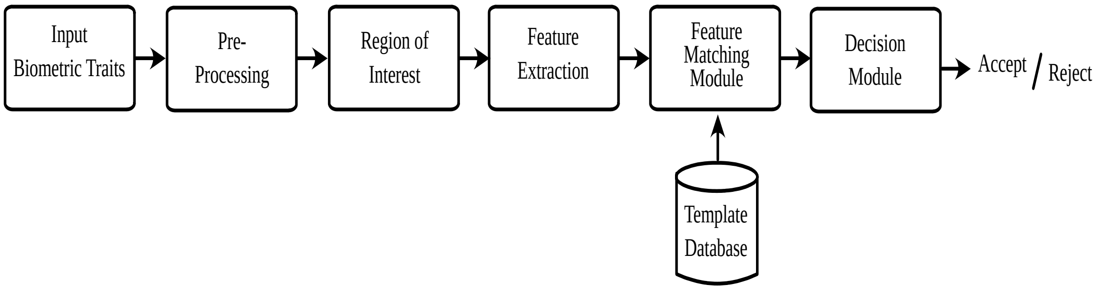


Figure.2 Steps Involved in a Biometric System during Recognition

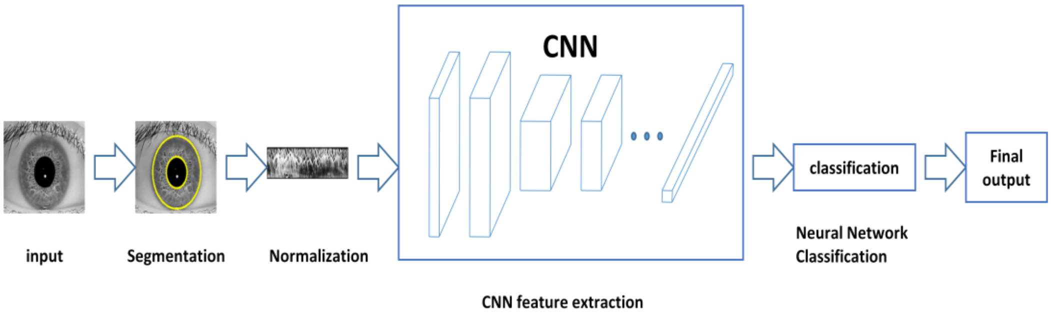


The ROI is the process of highlighting key and interesting features as a smaller region in a biometric characteristic that will further be used in a biometric system as matching features and then extracted features.

Thus extracted features will be compared against the feature database in the matching module to generate a match score and finally by using the match score Decision module will identify the authorized persons. These sequences of steps are shown in Fig.2. A biometric system offers two important functions, one of which is verification and the other is identification. Verification involves a one-to-one search (1:1), while identification is achieved when a one-to-many (1: N) search is performed by a biometric system [14]. A biometric system demonstrates that you are who you claim you are during verification. On the other hand, in identification, an individual attempts to claim that he or she is one of the individuals registered in the database.

4. Process Involved in Iris Systems

Figure.3 Process involved in Iris systems



The pre-processing on iris images is implemented by performing three stages: image enhancement, iris segmentation, and iris normalization shown in Fig.3 [15]. But before giving the input images to segmentation, the acquired images need to be processed to eliminate the noise during capturing. This work, also involving convert the color image (if the image is color) to the gray scale image, and a median filter is used to improve the quality of the image because brightness is not distributed uniformly and to remove some noise around the pupil as shown in Fig. 5.

4.1. Segmentation

To find the pupil-iris and iris-sclera boundary regions from the image a segmentation step was taken. The primary reason for doing this is that it would help to reduce the computations by identifying these regions instead of providing the complete eye picture as input to CNN, Previous research has shown that the error produced during the iris segmentation stage is propagated to all subsequent stages of recognition. Therefore the location of the iris area (identification of iris boundaries) plays an important move in enhancing the performance of an iris recognition system. To attain optimum efficiency, iris segmentation is often used as a significant pre-processing step in iris recognition. The iris is the annular portion between the sclera and the pupil. By applying any of the edge detection operators, the iris localization can be done and then circular Hough transforms to segment the iris [16].

A detection system used for the identification of lines and edges is the canny edge detector. Using the Canny edge detector, an edge map is created to form the input to extract the circle. The Hough transform is used in this paper to detect the boundaries of the iris and pupil. [17]. In Circular Hough Transform, in parameter space, the voting procedure is carried out. As part of this suggested segmentation work, a mixture of the canny edge detector, for an edge map, and circular Hough transformation is used. This strategy of segmentation not only extracts the iris region but also removes occlusions. The Circular Hough Transform is used to detect circles in image inputs. The circle candidates are chosen by "voting" in the Hough parameter space and then choosing the local limit in an "accumulator matrix."Because of the "Brute-force" method, the technique can be computer-intensive, where Circular Hough Transform measures any possible circles in the input image. For this purpose, the Canny Edge detector is first used in the input eye image to construct an edge map, which then makes Hough Transform to determine the Iris boundaries more quickly and more accurately [18].

The system looks for the Iris-pupil boundary within that circle after determining the Iris-sclera boundary. The Eq.(1) is the generalized expression for Circular Hough Transform, whereas the expansion for Eq.(1) is stated in Eq.(2) having the circle information

$$\mathrm{H}\ (\mathrm{a,b,r}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{h}\ (\mathrm{x_i, y_i, a, b, r}) \qquad (1)$$

Here (xi, yi) is an edge pixel and i is the index of the edge pixel Where

$$\mathrm{h}\ (\mathrm{x_i,\ y_i, a, b, r}) = (\mathrm{x_i}\ - \mathrm{a})^2 + \ (\mathrm{y_i}\ - \mathrm{b})^2 \qquad (2)$$

The Circular Hough transformation is used to determine the iris and pupil's centre and radius. The radius is denoted by r and the center of the iris is represented by (a, b) and the coordinates of the circle are $(\mathrm{x}_i,\ \mathrm{y_i})$. The pair of equations at Eq.(3) results in the expression of the circle equation in parametric polar form.

$$\mathrm{a = x + rcos(\theta)} \quad \mathrm{b = y + rsin(\theta)} \qquad (3)$$

The edge image in Hough space is used to cast votes for the parameters, with the central coordinates (xc, yc,) and the radius 'r' of circles passing through each edge point. They are capable of describing any circle by such criteria. In general, it is difficult for edge detectors to adapt to various situations. The quality of edge detection is heavily dependent on the lighting conditions, the presence of similar intensity objects, the density of the edges in the scene, and also the noise. To minimize the search space, the eye image must be improved both before and after the edge map is created. A 2D median filter is used in this work to smooth the eye image and reduce noise [2].

4.2. Normalization

Once the iris area has been successfully segmented from an image of the eye, the next step is to translate the iris region into fixed dimensions. For the reduction of noise, the fixed dimension of the iris area is important due to the dilation of the pupil. Daugman [4] suggested a homogeneous model of rubber sheets for normalization. This model maps each point from Cartesian coordinates to polar coordinates within the iris region. A rectangular image with angular and radial resolutions is a normalized iris image. Radial vectors are drawn along the field of the iris region, using the pupil center as a reference.

Normalization creates a 2-D array with horizontal angular resolution dimensions and vertical radial resolution dimensions from the iris region as shown in Fig. 4. The angular resolution is the number of radial vectors that travel across the iris field, while the radial resolution is the number of data points selected for each radial vector [15]. Remapping region of the iris to the polar coordinates from the Cartesian coordinates using Mapping and remapping from Cartesian to Polar coordinate system and the vice-versa is performed using the Eq.(4), Eq.(5), and Eq.(6)

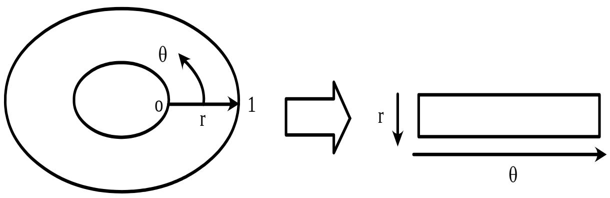
$$\mathrm{x}\ (\mathrm{r}, \theta) = \mathrm{r} \times \cos(\ \theta) \qquad (4)$$

$$\mathrm{y}\ (\mathrm{r}, \theta) = \mathrm{r} \times \sin(\ \theta) \qquad (5)$$

$$\mathrm{I}(\mathrm{x}(\mathrm{r}, \theta), \mathrm{y}(\mathrm{r}, \theta)) \rightarrow \mathrm{I}(\mathrm{r}, \theta) \qquad (6)$$

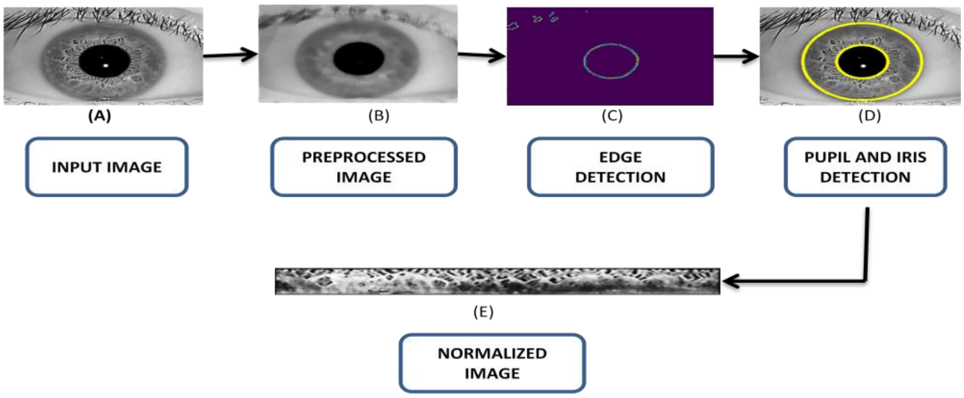
Normalization aids in the removal of dimensional differences that may occur when capturing an eye's image due to changes in lighting, camera distance, angle, and other factors. For the feature extraction process, normalization prepares a segmented iris image. The normalized image obtained is now improved to compensate for the low contrast, the poor source of light, and the position of the light source. Histogram equalization is applied to reduce the reflection noise. Finally, we get a smooth image to select the correct size of the edge analysis.

Figure.4 Daugman's rubber sheet model



In this step, the circular iris texture is transformed into a two-dimensional iris sheet with fixed dimensions. The detected iris is unwrapped into a rectangular area by changing the Cartesian coordinates to polar coordinates [19]. In our proposed work, the iris-segmented image is normalized to a fixed rectangular block of size 432-38. As per the discussion in Fig. 3.The outputs of preprocessing steps shown in Fig. 5.

Figure.5 Output of preprocessing steps



4.3. Feature extraction and classification using CNN.

If a normalized iris image has been acquired, to obtain the feature extraction a deep learning technique is used with repetitive neuron blocks in the form of convolutional, pooling, and fully connected layers with a Softmax classifier. Each layer in the image represents different levels of visual content, with later layers encoding finer and more abstract information and earlier layers retaining coarser information.

One of the main reasons for CNN's success in computer vision is that these deep networks are highly adapted to capture and encrypt complex imaging functions with more layers and millions of parameters with greater efficiency.

The structure of the proposed CNN includes Convolutional layers, max pooling, and fully connected layers. The kernel is nothing but a filter used to extract features from images in the Convolutional Neural Network. The kernel is a matrix that passes over the input data, executes the dot product with the sub-region of the input data, and gets the output as the dot product matrix. A filter is a collection of learning weights in the CNN sense that are learned by the back propagation algorithm. Any filter can be thought of as a single template/pattern that is stored. When we combine this filter over the corresponding input data, it effectively means trying to figure out the similarities between the stored template and the different input locations. The number of filters is the number of neurons since each neuron conducts a different convolution (more specifically, the input weights of the neurons form convolution kernels) on the input to the layer.

The number of pixels that we slide through the kernel is known as the stride. Usually, the stride is kept as 1, but we can raise it. If increased, the image size may need to be increased by a few pixels to fit the kernel at the edges of the image. This increase is called padding

Activation features make it possible for the network to use essential data and to delete meaningless data points. In comparison with other activation functions, the main advantage of ReLU is that not all neurons are activated simultaneously so that neurons are disabled only when the linear transformation is less than zero. It must be computationally efficient since millions of data points are often trained by the neural network and allow the network to converge very quickly. Adding nonlinearity to the network is the primary application of the activation function of ReLu.

In neural networks for multi-class classification, which require the classification of inputs into multiple categories. Generally, we use Softmax and cross-entropy along with it. A cross-entropy loss function is used because it is an acceptable loss function for the classification task.The Softmax activation function returns the output probabilities of the inputs. The probabilities will be used to find out the target class. It will be the most likely final output. The sum of all these probabilities must be equal to 1. It is preferably used in the classification of several groups.

5. Proposed System Architecture

To find the best CNN configuration in the proposed methodology parameters for iris recognition tasks that have a major impact on the performance of CNN are Input Image size and Training methodology includes hyper parameter tuning, optimizer used, and Learning rate schedulers.

5.1. Input Image Size

The size of the data image is one of the hyper parameters in the CNN that has a major effect on the neural network's speed and accuracy. The input image in this project is (200x150) pixels in size. Each Convolution layer has zero padding to monitor the spatial scale of the input and output volumes. The images are from the

IITD iris dataset and CASIA V1.0.The iris images in this database were taken from the IIT Delhi students under different environmental conditions impacting the iris and employees in multiple environmental conditions. In CASIA-V1, each file is saved in BMP format with a resolution of 320*280 pixels and contains 756 iris images from 108 eyes. Using the self-developed CASIA close-up iris camera system, seven images are obtained in two sessions for each eye shown in Table 1.

Table 1. The specifications of the datasets used

Data base	**IITD**	**CASIA V1.0**
Number of input classes	224	108
Images per class	(10 for each class)	(7 for each class)
Total Number of Images	2240	756
Size of input image/format	320x240/BMP	320x280/ BMP

5.2. Training Methodology

In this work, 80 percent of randomly chosen samples for training and 20 percent of samples are selected for validation from training data and the remaining 20 percent of unseen samples are used for testing. Validation collection is used to interpret the ability of the network to configure and store weights that work best with the least validation error. Identifying the best network architecture of CNN is also one of the main parameters of training methodology. The below Fig 6 shows the network design of the proposed work.

The variables that control the network architecture or topology are known as hyper parameterssuch as the number of layers and nodes in each hidden layer, as well as variables that control how the network is trained (Eg: Learning Rate). Before training, hyper parameters are set up (before optimizing the weights and bias).The hyper parameters and its values of the proposed network is given in Table 2.

Figure.6 Proposed CNN architecture

Layers/Operation	**Hyper parameter**	**Values IITD**	**Values CASIA**
Convolutional	Filter size	3* 3	3*3
	No of Kernels	32, 32	32,64,128
	Fully connected(FC) layers	512	512,256,108
Activation function	used	ReLu	ReLu
pooling and its size	Max Pooling	2	2,2,2

In the proposed training architecture, the key steps were followed for implementing iris recognition using SGD optimization and hyper parameters.

1. Splitting dataset as training, testing, and validation sets.
2. Used the hyper parameters mentioned above to train the network.
3. Using validation, check the configuration.
4. The total epochs are set to 50.
5. After getting the minimal error using the validation set.
6. Finally using the test, evaluate the model set and saved the weights.

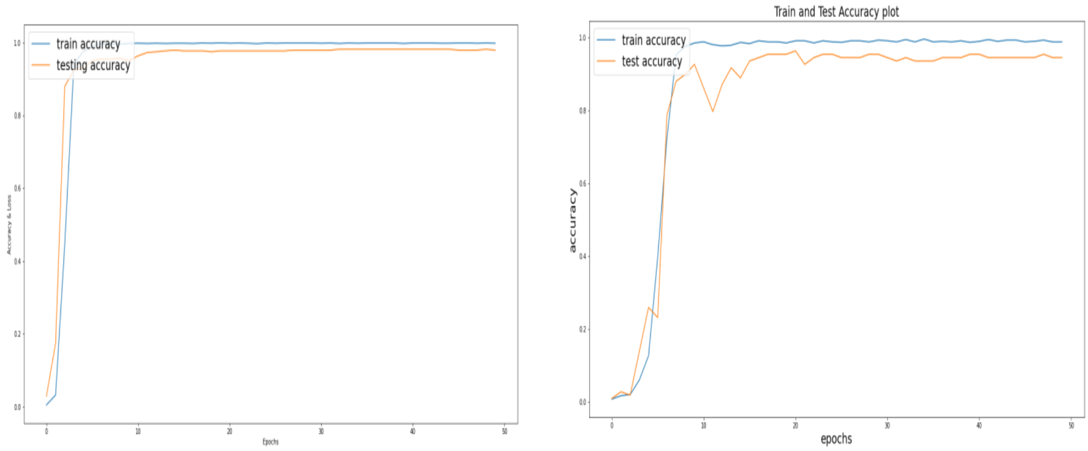
The dropout technique has been introduced along with these parameters in this work. This helps to avoid over-fitting and is positioned after the first hidden layer on the training package. By ignoring the 0.3 probabilities of the nodes, including their connections.

In our experiment, time-based learning rate decay has been used. The Learning rate is updated after every epoch with a starting learning rate of 0.01. We can often improve our classification accuracy while also reducing the effects of overfitting by using learning rate decay. Thereby increasing the ability of our model to generalize.

6. Results and Comparison

The proposed architecture training and testing accuracy plot of iris recognition for the IITD database and CASIA V1.0 shown in Fig.7. The accuracy of this proposed architecture is 98.05 percent for IIT and 95.5 percent for CASIA.

Figure.7 Proposed architecture training and testing accuracy plot: (a) IITD and (b) CASIA V1



(a) (b)

Table 3 shows a comparison of the results of our proposed method with current state-of-the-art methods applied to the iris dataset.

Table3a.Comparison with the existing Methods (IITD).

Method	Accuracy (%)
Transfer Learning Approach[9]	95.5
Haar Wavelet , Kumar and Passi [20]	96.6
Log Gabor filter ,Kumar and Passi [20]	97.2
Statistical Feature Extraction , Bansal et al.[21]	97.86
Proposed Deep Learning Approach	98.05

Table3b. Comparison with the existing Methods (CASIA)

Method	**Accuracy (%)**
FFT,Lemmouchi Mansoura, et al.[22]	**77.50**
PCA,Aniket S.Buddharpawar et al.[23]	85
2D Gabor filter with SVM classifier ,Asim Ali Khan et al.[24]	90.25
2D Gabor filter with Artificial Neural Network,Asim Ali Khan et al.[24]	83.65
Proposed deep learning approach	95.4

7. Conclusion

In this work, we introduced an iris recognition method that uses a deep learning approach that authenticates the identity of an individual. The suggested method by adding localization to the iris using a Circular Hough Transform together with a canny edge detector followed by an automated extraction feature using CNN. Overall precision is improved by the hyper parameter tuning and the learning rate scheduler. We will focus on more real-world databases as part of future work to associate our findings obtained with them. To improve the accuracy of the proposed method, we will also work on new methods such as multimodal biometric authentication with suitable levels and methods of fusion.

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