Iris Recognition using Hough Transform and Neural Architecture Search Network

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***Abstract* – Biometric authentication technology is a key in security devices and systems. Each individual has unique biometric identifiers and irises are among them. Each Iris is unique in its own. In order to exploit them, for the purpose of identification, precision plays an important role to avoid errors. In this paper, a model has been proposed for recognizing irises and is capable of distinguishing and filtering only relevant images. These images are processed through steps of segmentation and classification. Through the combined means of Deep Learning Neural Architecture Search Network (NASNet) and Morphological Image Feature Extraction techniques, the developed system performs real-time iris segmentation and detection with cent percent accuracy. The process begins by taking input image and running through the segmentation process, where the Region of Interest (RoI) Iris images are extracted from the CASIA Iris Interval Dataset and the output is fed to the applied Convolutional Neural Network (CNN) for classification and identifying the batch of images. The Iris Recognition model has been validated and trained successfully.**

Keywords – Iris Segmentation, Image Processing, Convolutional Neural Network, Iris Recognition, Hough Transform, Neural Architecture Search Network.

I. INTRODUCTION

Authentication plays an important role in guaranteeing the Security aspect where verification and identification are crucial. Use of Biometric Authentication is on a steady rise and has proven to be a secure and somewhat foolproof method of identification [1]. Examples include facial recognition, fingerprint scanning, voice recognition, hand-geometry recognition, Iris recognition, etc. With increasing requirements of much more efficient and secure technologies, researches are being done for enhanced and advanced approaches in biometric identification.

Use of Artificial Intelligence enables utilizing advanced algorithms efficient in special case scenarios that is either not possible or difficult to achieve with traditional algorithms [2]. We have made use of Convolutional Neural Network (CNN) Deep Learning Algorithm to obtain high efficiency, low loss and high precision Iris recognition. The specialty of CNN is that it automatically detects the important features without any human supervision. This is made possible by applying Deep Learning, a subset of Machine Learning algorithms which uses multiple layers to progressively extract higher-level features from the raw input [3].

This paper proposes a new end-to-end eye detection and iris recognition model using Hough Transform and morphological operations of opening and closing for identifying image of an eye, followed by Neural Architecture Search Network (NASNet) CNN Model for classifying recognizing and testing extracted Irises.

Rest of the paper as following sections Introduction and literature survey is explained in section 1 and section 2 respectively. Overview of the model is explained briefly in section 3. Further proposed model is explained in section 4. Results and discussion is explained in section 5 and finally work has been concluded in section 6.

II. LITERATURE SURVEY

Various techniques exist for iris segmentation, Daugman et. al [4] proposed the Integro-Differential Operator method for identification of appropriate iris radius with two Hough circles in the respective upper part and lower part of the iris in the segmentation process.

Ehsaneddin Jalilian et.al [5] proposed a new approach of segmenting iris with a precise parameter of off angle for CNN classification. Further modified and settled the obstacle of the off angle iris images and the gaze angle of iris.

Following the work of Daugman [4], Jawad Muhammad et. al [6] expands the segmentation by compensating the real time adverse environment noise on CASIA.v4-distance, UBIRIS.v2 datasets which suppress the noise in segmentation.

Domain adaptation (DA) for CNN classification in [7] is proposed by Ehsaneddin et.al which is based on two-pixels classifier which is linear and non-linear approaches.

Including DA in a training model improves the transferable learning (TL) as proposed by Jalilian et. al [5] drastically.

Daniel et.al [8] addressed deep residual network-based iris segmentation using Gabor-iris matching proposed model. The Hamming distance, union and normalization were quite better over the default algorithms mainly OSIRIS [9], IFPP [10] with the introduction of Gabor-matching.

III. MODEL OVERVIEW

The model is divided into two parts. The first part is to undergo eye detection in the given image, followed by iris detection. The image of the eye is converted to monochrome, followed by Iris boundary detection and Hough Transform for detecting circular shapes resembling Iris and cornea.

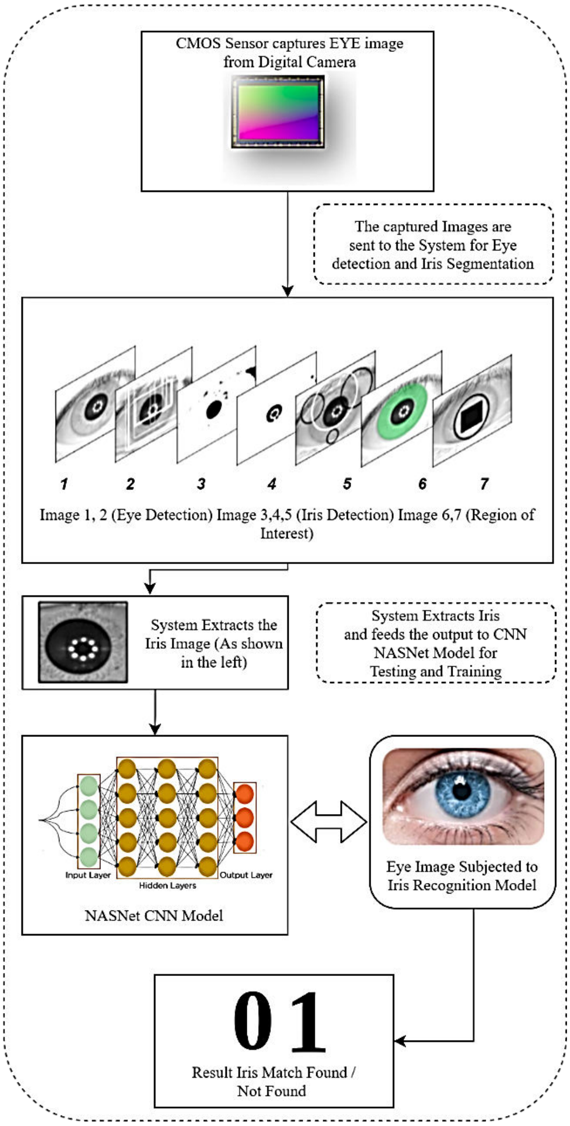

Figure 1. Flow Chart for the Proposed Model

Morphological operations of Opening and Closing to narrow down the relevant iris region is performed. The final region of interest (RoI) is extracted. and segmenting by the means of feature extraction and stored into a 200x200 pixels dimension .jpg format image.

The second part is classification. The extracted features are fed into Convolutional Neural Network (CNN) to train the model and finally test the sample irises. This data is fed to the trained NASNet CNN Model for testing.

Our CNN model consists of 15 layers which are divided into four parts namely, convoluion layer, filter layer, pooling layer and fully connected layer. In convolution layer the raster scan is performed over each pixel and pixels are normalized by arithmetic operations.[19] Filter layers comapares the input image by patching through filters and negative pixel values are removed from the matrix. In pooling layer the size of the image is reduced by passing the processed matrix in window filter for feature extraction [20]. Lastly our model has a fully connected layer, in which classification is done by connecting each neuron network in CNN.

NASNet algorithm is capable of classifying 1000 different classes of objects in a single search and can provide immense advantage over a wide range of image search. This classification algorithm uses an input size matrix which is obtained by pre-processing of data (in this paper it is an iris image after extracting) and sets the shape as 331-331 of that image input matrices. NASNet performs better than other CNN Models which provides us 2-3% of improvement in accuracy [2].

IV. PROPOSED MODEL

A. Eye detection

The human iris is a thin circular diaphragm located between cornea and lens. Different parts of human eyes have been labelled in Figure 2. For an individual, each characteristic of eye is unique. The RoI (Iris) is a finely detailed structure of an iris which is developed by random process and not developed genetically.

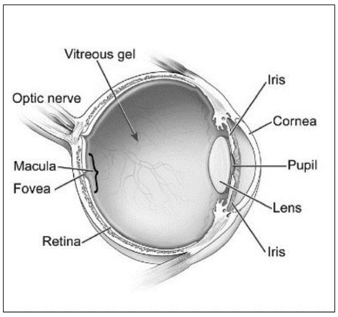

Figure 2. Anatomy of a human eye

In this model, Haar Cascade is used because of low-computational requirements for Eye detection in dataset image, that will identify eye features with high accuracy. See Figure 3. [11] The model determines whether the image has the eye identified.

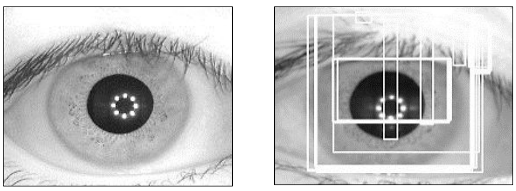

Figure 3. Eye Detection process output. Input image (*left*). Eye detected (*right*)

B. Iris detection

The iris detection marks an important step for acquiring biometric data. The RoI is between the pupil and the limbus as shown in Figure 3.

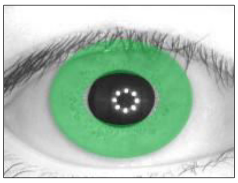

Figure 4. Iris Region of Interest (RoI)

For the purpose of Iris Detection, Circular Hough Transform (CHT) has been applied. CHT has numerous applications and has been applied to perform pattern detection. The CHT detects radius and then plots circles at the edge. This is accomplished using the equations (1) and (2) given below.

$$(x - a)2 + (y - b)2 - r2 = 0 \tag{1}$$

Where, 'r' is the radius of the circle. 'a' and 'b' are the coordinates of center. 'x' and 'y' are the possible points of the circle. They can be obtained as follows.

$$x = a + r\,cos(\theta) \tag{2}$$

$$y = b + r\,sin\,(\theta)$$

The model processes the output image taken from previous step of eye detection. CHT is applied to the sample to make sure that iris is detected and highlighted in Hough Circles of white color, while the irrelevant Hough Circles identified are marked in black colors, shown in Figure 5. Also, this process rules out any possibility of closed eye or any artifacts appeared in the image and the successfully identifies iris images that are sent to the next step of the model.

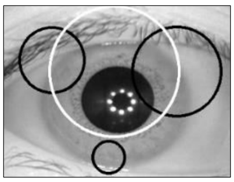

Figure 5. Hough Circles in RoI

C. Iris Segmentation

Iris Segmentation is performed for recognition of features. The test image after passing the above two steps is subjected to segmentation by applying Morphological Process. The segmented images are fed into the Convolutional Neural Network (CNN) for training and classification. In Image Processing, morphological operations provide analysis and structure of images. For example, in cellular biology and medical imaging [12]. Here, we apply the process of Opening and Closing.

The operation of Dilation makes the object to grow by size. The growth depends on the nature and shape of the structuring element. In the following equation, the dilation of image X by structuring element Y is defined:

$$A \oplus B = \{z \in E|\ (B)^{s}{}_{z} \cap A \neq \Phi\} \tag{3}$$

Erosion is a morphological operation which removes a pixel from the boundary of an object being identified and exposed. The erosion of A by B, B AΘ is given below

$$A \ominus B = \{x|(B)\ x \subseteq A\} \tag{4}$$

Opening is morphological operation performed by Erosion followed by Dilation. Opening of A by B over an image is represented as:

$$A \circ B = (A \ominus B) \oplus B \tag{5}$$

Closing is a morphological operation performed by Dilation followed by Erosion. Closing of A by B over an image is represented as:

$$A \cdot B = (A \oplus B) \ominus B \tag{6}$$

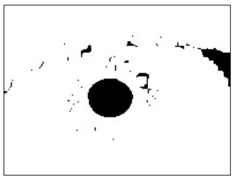

Figure 6(a) Opening of an Eye

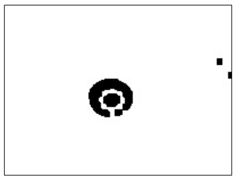

Figure 6(b) Closing of an Eye

Figure 6(a) and Figure 6(b) represent the respective opening and closing operation performed on the same eye sample using equations (5) and (6). As it is observed, opening is enhancing the focused iris which is saturated by erosion giving us an immensely segmented iris. While in closing operation, the boundary pixels thus dominate and hence this operation can be used in filling small gaps in an image.

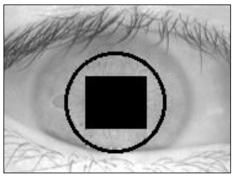

Figure 7. Model Segmented Region of Interest

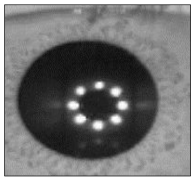

Figure 8. Extracted Iris

With a black mask on Figure 7, the required Iris region has been segmented and is extracted as depicted in Figure 8. Our required RoI Iris region has been acquired by going through the steps listed above.

D. Iris Classification

Neural Architecture Search Network (NASNet) is a new CNN architecture that reached State-Of-The-Art (SOTA) results on classification datasets. The model has been trained on more than a million images from the ImageNet database.

Deep Neural Networks have proven to surpass the human error rates in recent years in the fields of Image Processing [13][14]. The training of the model is directly proportional to the number of epochs made for training.

Our paper addresses the use of reinforcement learning (RL) in the evolution of the NASNet classification. Reinforcement learning is an iterative converging algorithm mostly utilized in NAS architecture, which in the search strategy process iterates the dataset of the transition layer [21]. The NAS architecture of this paper consists of 15 hidden layers in the algorithm which converges with RL till the dataset is converged on the input matrix of the image size (331-331).

In our training procedure we adopted Adam's optimizer with the factor of 0.8, batch size of 32 and epochs to train the model as 80 and learning rate as 0.001. For NASNet, this paper utilized weights factor from standard NAS architecture learning which can easily and efficiently (w.r.t time) can train the model with less epochs. Software activation is used in the last transition layer of NAS architecture.

V. RESUTS AND DISCUSSION

The proposed Iris Classification and Segmentation system was subjected to training and testing from the CASIA Iris-Interval dataset which is a part of CASIA version four [22]. The dataset consists of forty-two individual subjects each having 18 iris images of left and right eyes. The dimension of each image is 320x280 pixels. Overall number of samples is 1344. The output resolution of irises is 200x200 pixels in monochrome. For testing purpose of the trained NASNet model, 4 random images from each individual class are chosen. The output size of the NASNet Network is a matrix of dimension (3x4x4x672).

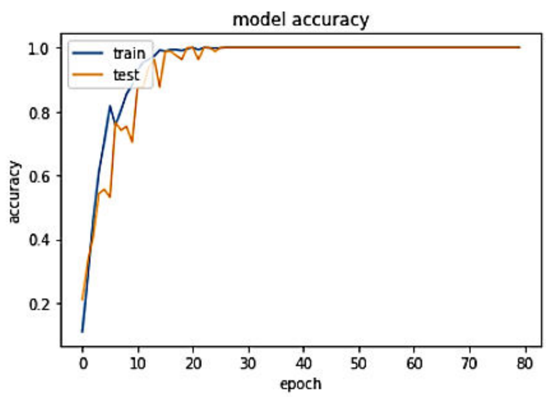

Figure 9(a). Model Accuracy v/s Epoch for train and test cases.

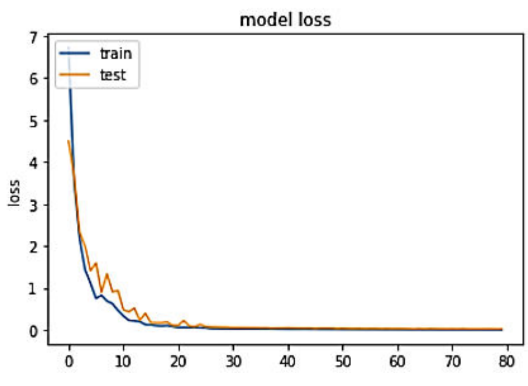

Figure 9(b). Model Loss v/s Epoch for train and test cases.

Model accuracy is a parameter used to determine performance of a machine learning model by identifying relationships and patterns between variables in a dataset. Figure 9(a) and Figure 9(b) are the plot of model accuracy and model loss respectively with increasing number of epochs. It is observed that at 21st epoch, a cent percent accuracy is achieved and the losses drop to 0 percent.

TABLE I. COMPARISON WITH RECENT METHODS

S. no	Method	Classification Accuracy	Model loss	Ref.
1	InceptionResNet V2	92.59%	0.2733	-
2	InceptionV3	95.06%	0.1525	-
3	VGG16	95.06%	0.2112	-
4	Xception	97.53%	0.0468	-
5	Uncertainty theory method	99.60%	-	[15]
6	KL Tracking	99.75%	-	[16]
7	Krawtchouk Moments with Manhattan distance	99.80%	-	[17]
8	k-nearest subspace, sector based and cumulative sparse concentration	99.43%	-	[18]
9	NASNet (Proposed Model)	100%	0.0262	

The model accuracy is obtained using equation (7). For further analysis, we have inter-compared our proposed model with other convolutional neural network techniques as listed in Table 1. From comparison, we observe that accuracies range within 92.59% to 99.43% on CASIA Iris Interval dataset.

$$\text{Accuracy} = \frac{\text{Number of Correctly Classified Images}}{\text{Total number of images}} \times 100 \quad (7)$$

Figure 10 shows the sample input eye images from CASIA Iris-Interval dataset. The accuracy parameter is used to check the F-level in the proposed model. The model achieved 95.05% accuracy in extracting the iris from the given set of images. The model achieved accuracy of 100% in classifying the images.

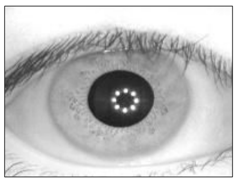

Figure 10. Sample Eye Image from CASIA Iris-Interval

VI. CONCLUSION

This paper has proposed iris segmentation and recognition via classification technique which provide us with the highest achievable accuracy on CASIA Iris Interval Dataset. The paper deals with iris segmentation procedure through Hough circles and morphological operations. The classification is achieved through Neural Architecture Search Network (NASNet) model which when subjected to increasing number of epochs achieves 100% accuracy. Thus, making the system reliable and robust under tested scenarios.

This paper starts from the scratch by capturing an image, segmentation process identifying the eyes, and pre-processing the iris region of interest for reducing processing time drastically and extract features from the same. Finally, the classification of the iris using NASNet Model architecture as classification algorithm has achieved 100% accuracy in detecting and classifying in our proposed model on dataset of 42 classes having 18 eye samples in it.

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