

New full Iris Recognition System and Iris Segmentation Technique Using Image Processing and Deep Convolutional Neural Network

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Available online at: www.isroset.org

Received: 28/Jan/2020, Accepted: 14/Feb/2020, Online: 30/Mar/2020

Abstract- Iris recognition is a technology used in many security systems. Irises are different among all people every person has a unique iris shape and there is no two irises have the same format. In this paper, a new model is introduced in iris recognition to make this technology easy for anyone to use it, especially that any image can be used in the model and the model filter itself and choose only the images that pass the model filters. This paper presents an iris recognition system from the beginning of eye detection to the end of recognizing the iris images. This paper also presents a new process to make iris recognition which is a blend between image processing techniques with deep learning to make iris Recognition. Also, this paper represents a new iris segmentation technique that detects the iris images efficiently with high accuracy. The iris recognition model is beginning an eye detection process then the iris detection process takes place which detects the iris inside the eyes then iris segmentation process gets iris images that will be saved and used in the last process which is responsible for iris classification using convolutional neural network. The iris recognition system was tested on well-known data sets: Casia Iris-Thousand, Casia Iris Interval, Ubiris Version 1 (v1) and Ubiris Version 2 (v2).

Keywords: Iris Recognition, Iris Segmentation, Computer Vision, Convolutional Neural Network, Image Processing

I. INTRODUCTION

In recent years iris recognition has an important place especially in the field of biometric pattern recognition [18]. Iris recognition plays an important role in many applications It helps in the identification of different persons with high accuracy as each person has unique iris featured and at 1 in 10^{72} the probability for the existence of two similar irises [9][23]. The iris has random morphogenesis which makes each person has a unique pattern [10].

Iris recognition gives high accuracy more than other human characteristics in user authentication like Fingerprint and handwriting [8]. A lot of governments and institutions using biometric technology in their security systems as this technology has high accuracy [36].

This paper introduces a new and full system for Iris recognition which begins by eye detection and then iris detection and if the image successfully passes these steps it will pass through iris segmentation step and the final step is iris classification using convolutional neural networks. This paper introduces a new iris segmentation method to extract features from the image.

In section 2 related works are discussed and in section 3 overview of the proposed model in section 4 detailed explanation of each step of the model in section 5 contains the results and conclusion in section 6.

II. RELATED WORK

Hugo and Luis et al. [10] introduced the relation between error rates and the segmentation process and there is an increase in the error rates when the iris is inaccurately segmented. In [19] CNN was used in iris recognition and it was observed that many weakly correlated CNN matching scores can be obtained which together provide a strong model where sparse linear regression techniques are used in this paper to solve many problems like regularization.

Hugo and Luis et al. [23] studied the relation between the sampling rate in the iris normalization stage and the overall accuracy of iris recognition. Hugo and Luis et al. [17] proposed a new iris classification model which makes six regions from segmented and normalized iris where fusion rule is used to achieve iris classification.

In [15] discussed the iris image preprocessing for iris recognition on unconstrained environments using deep representation. This approach begins by segmentation and normalization then data augmentation is used to increase training samples feature extraction is done using two CNN models and cosine distance is used for classification.

Ahmed Sarhan et al. [18] proposed an algorithm that uses discrete cosine transform (DCT) to extract distinctive features from the iris image then the extracted feature to vector is applied to an ANN for classification.

Int. J. Sci. Res. in Multidisciplinary Studies

In [32] a new segmentation algorithm was used to detect the pupil which depends on a threshold that detects the black rectangular area in the pupil where the grayscale values within the pupil are very small. This paper uses a neural network to recognize the iris patterns the architecture of the neural network is two hidden layers the first hidden layer contain 120 neurons and the second one contain 81 neurons.

III. MODEL OVERVIEW

the iris recognition model begins by detection process which tries to find eyes in the images collected by camera then the second process is iris detection in this phase iris inside eyes images are detected to be ensure that the eyes have visible iris that could be segmented in the next steps the third process is iris segmentation that will be used to extract features that will be used in the last process by the convolutional neural network (CNN) model to train and test iris images.



Fig 1 shows the architecture of the iris recognition system

IV. IRIS RECOGNITION MODEL

4.1. Eye detection

Eye detection has a lot of different applications. Iris recognition is one of these applications [7]. The model uses haar cascade classifiers to detect eyes as these classifiers are fast, don't need a lot of computational time and give high accuracy [6].

Images that come out from camera pass through haar cascade classifiers that detect eyes in these images. This stage will ensure that the images contain eye. the image will pass to the next step if and only if the classifier detects eyes. Figure 2 shows the output of this process.



Figure 2 shows iris detection process output

4.2. Iris detection

Iris detection is a very important step in the model as without iris images training deep neural models will be worthless. We can define the iris as it's the region between the pupil and the rest of the eyes [4]. Hough transform has a lot of applications it has been used to detect different patterns for example lines and circles [5]. We can define the Hough transform algorithm mathematically as follows:

For each pixel (x,y) the Hough transform algorithm use accumulator to detect r



Fig 3 shows Hough transform parameters where:

r: distance from origin to the closest part on straight line Θ : is the angle between x axis and r For $\Theta 0^{\circ}$ to 360°

 $r = x \times \cos(\Theta) + y \times \sin(\Theta) \quad (1)$ Accumulator(r, Θ) = Accumulator(r, Θ) +1 (2)

The model takes the images detected in the last phase and applies Hough transform on these images this phase is ensure that there is an iris inside the eyes because it's possible that the eyes are closed or anything else that

Int. J. Sci. Res. in Multidisciplinary Studies

makes the iris doesn't appear in the image so this phase detect the appearance of the iris inside the eyes and the image will pass to the next step if it successfully pass this step. Figure 4 shows the output of this process.



Figure 4 shows iris detection process output

4.3. Iris Segmentation

Iris segmentation plays the most important role in iris recognition as the features extracted from the iris segmentation process will be used in the classification process so the accuracy of classification will depend on the quality of the segmented images

If the image passes the first and second steps successfully it will reach this step. In this paper, a new segmentation algorithm is introduced which contains three steps: Choosing Threshold, Morphological Process, and Contour Detection.



Fig 5 shows iris segmentation architecture

Morphology in image processing provides structure and analysis of images where it has a lot of applications in many areas like medical imaging and cellular biology [33] [34]. Operations performed in morphology are interactions between object and structuring elements.

In this paper opening and closing operations are used which we can define them mathematically as follows:

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If A and B represent grayscale image and structuring element respectively in Z^2 and E is the Euclidean space where A exist then :

We can define dilation as:

$$A \bigoplus B = \{ z \in E | (B)^{s} \cap A \neq \emptyset \}$$
(3)

We can define erosion as :

$$A \ominus B = \{ z \in E | Bz \subseteq A \}$$
(4)

From equations (1) and (2) we can defined opening and closing operations as:

Opening between $(A, B) = ((A \ominus B) \oplus B)$ (5)

Closing between $(A, B) = ((A \oplus B) \ominus B)$ (6)



figure 6 a- example of opening operation b- example of closing operation

Iris images captured by the camera or any sensor that have many differences and these differences are many and many such as the environment that surrounds the iris images that have many variables, the shooting distance that can be far or near and the lighting and there are many other things so it must that the algorithm be as variable with all of these variables to capture or take correct information and not be affected by any other factors, and this is the algorithm presented in this paper.

The algorithm uses morphological techniques to extract iris information but in a way that makes it suitable for the changes mentioned before.

The morphological process is begun by defining a threshold for the image then makes opening and closing morphological operations then a bitwise OR operator between opening and closing images.

So for each image, the algorithm begins by defining golden reference which is the sum of all pixels in the image when it passes through the morphological process with threshold = zero. This threshold begins to increase in working reference and it's compared with golden reference this process of increasing the threshold will continue until the working reference begins to be different from the golden reference by a certain amount then the increase of the threshold stops and working reference will be chosen to the next step. The output image from the last step will be taken and the contour border algorithm which was proposed in [35] will be applied to it. The final results are shown in figure [7].



Figure 7 shows output from segmentation process from different datasets a- Ubirs v2 b- Casia-Iris-Thounad c-Casia-Iris-Interval d- Ubirs v1

4.4. Iris classification

Deep neural network models have become a very strong tool in many applications. Image classification is one of the applications of deep learning [1] [2].

The model uses a convolution neural network as it can understand unique features in images [3]. The model uses a convolutional neural network (CNN) for iris recognition as CNN will differentiate between different classes.

In this process, a pre-trained convolutional neural network model DenseNet-201 is used for iris classification [39]. table 1 shows the architecture of DenseNet-201 which contains four dense blocks and three transition layers. A flattening layer and a dense layer followed by a softmax layer are added on the DenseNet-201 bottleneck output features.

In the training process Adam optimizer was used with $beta_1=0.9$, $beta_2=0.999$, learning rate = 0.001, batch size= 32 and number of epochs = 30. Softmax activation function used in the last layer. Data augmentation technique was used in data sets which is a change in the illumination of the images before the training process.

Table 1 shows Dense-Net Architecture.

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201		
Convolution	112×112	7×7 conv, stride 2				
Pooling	56 × 56	3 × 3 max pool, stride 2				
Dense Block (1)	56 × 56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$		
Transition Layer	56 × 56	1 × 1 conv 2 × 2 average pool, stride 2				
(1)	28×28					
Dense Block (2)	28 × 28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$		
Transition Layer	28×28	1×1 conv				
(2)	14×14	2×2 average pool, stride 2				
Dense Block (3)	14 × 14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$		
Transition Layer	14×14	1 × 1 conv				
(3)	7 × 7	2 × 2 average pool, stride 2				
Dense Block (4)	7 × 7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$		
Classification	1×1	7 × 7 global average pool				
Layer		1000D fully-connected, softmax				

V. RESULTS AND DISCUSSION

The proposed iris model was tested on four datasets which they can briefly discuss as follows:

1- Ubiris Version 1 (v1):

Ubiris v1 contains 1877 images from 241 subjects the dataset contains two sessions. Session 1 was used only in this paper because session 2 contains more images and this will make an unbalanced dataset so only session 1 was used which contains 1214 images. The images were collected using a Nikon E5700 camera and focal length = 71mm and image resolution = 800×600 pixels [38].

2- Ubiris Version 2 (v2):

Ubiris v2 is the extension of ubiris v1. Ubiris v2 contains 1877 images from 241 subjects the dataset contains two sessions. For the same reasons in ubiris v1 only session 1 was used in ubiris v2. The images were collected using Nikon Canon EOS5D camera and focal length = 400 and image resolution = 200×150 pixels [37].

3- Casia Iris-Thousand:

Casia Iris-Thousand is part of casia version 4 which contains six subsets. Casia Iris-Thousand contains 20000 iris images from 1000 subjects which were collected using IKEMP-100 camera with resolution 640×480 pixels .

4- Casia Iris Interval:

Casia iris interval is part of casia version 4 which contains six subsets. The number of subjects used in this paper = 42 each subject has 18 images. The images were collected using casia close-up iris camera with resolution 320×280 pixels.

Table 2 shows the information on images on each dataset before it pass to the iris classification process

Dataset	Number Of Classes	Number of Samples	image size before training process In Pixel	output size from the Dense-Net Network	Test Image Per Class
Casia Iris Interval	42	1344	200×200	2×2×1664	3 to 4
Casia V4 Iris- Thousand	1000	40000	70×70	6×6×1664	2
Ubiris V1	241	2428	200×200	6×6×1664	1 to 2
Ubiris V2	241	2428	200×200	6×6×1664	1 to 2

Int. J. Sci. Res. in Multidisciplinary Studies



Figure 8 shows example of different datasets a- Ubiris v1 b- Casia Iris-Thounad c- Casia Iris-Interval d- Ubiris v2

The parameter used to check level f the model in iris recognition is accuracy



Fig 9 shows the model accuracy and model loss with the number of epochs for Casia Iris-Thousand



Fig 10 shows the model accuracy and model loss with the number of epochs for Casia Iris Interval



Fig 11 shows the model accuracy and model loss with the number of epochs for Ubiris Version 1



Fig 12 shows the model accuracy and model loss with the number of epochs for Ubiris Version 2

Figures 9, 10, 11 and 12 represent the train and test accuracies and losses with the number of epochs on Casia Iris-Thousand, Casia Iris Interval, Ubiris Version 1 and Ubiris Version 2 respectively. Accuracies achieved in the test set are 99%, 100%, 99.32% and 98.29% on Casia Iris-Thousand, Casia Iris Interval, Ubiris Version 1 and Ubiris Version 2 respectively.

The test accuracies will be used in comparison to other iris recognition systems. Table 3 shows a comparison between different methods of iris recognition on each dataset used in this paper. Our proposed iris recognition system performs better than other methods on each dataset.

The results show that the accuracy range on all datasets from 98% to 100% which indicates that the proposed model is strong as it tested on different datasets and environments.

6. Conclusion

This paper proposed a new iris recognition system which performs high accuracy on different public datasets. The paper also proposes a new iris segmentation method which affects the final accuracy on each dataset. The performance of the proposed iris recognition model is better than other methods. the newly proposed iris segmentation method performs high accuracy which makes significant results in the classification step. All the methods on iris recognition focus on iris classification and iris segmentation but there is no methods focus on steps before that in this paper the proposed method takes a full journey from identifying the eyes to detecting iris then extracting iris features then classify the iris so the proposed iris recognition system is full method which can be tested on any types of images. In table 3 there are different methods and approaches to make iris recognition and the proposed method perform the highest accuracy among all other methods. The propsed model achived accuracy on Casia Iris-Thousand, Casia Iris Interval, Ubiris Version 1 and Ubiris Version 2 that is higher than other models in table 3.

Table 3 comparison between different iris recognition systems

Reference	Method	Recognition				
Reference	Wiethou	Accuracy				
Casia Iris-Thousand						
[25]	DenseNet 1	98 80%				
[14]	vgg net 2	90%				
[27]	Capsule 3	83.1				
[26]	M FGM 4	09.1				
[20]	Alox Not 6	98.8070				
[27]	MiCoPo Not 7	9870 88700/				
[J1] Proposed	MICORE-INEL /	000%				
Cosio Inio Intony	Proposed 99%					
Casia Iris-Interval						
[13]	uncertainty theory	99.60%				
[10]	method 14	00.75%				
[12]	KL Tracking 16	99.75%				
[24]	Krawtchouk	99.80%				
	Moments with					
	Manhattan distance					
	5					
[16]	k-nearest subspace,	99.43%				
	sectorbased and					
	cumulativesparse					
	concentration 17					
Proposed		100%				
Ubiris v1						
[30]	HSV color space 10	97.43%				
[28]	shape analysis 11	95.08%				
[21]	Gabor filter 12	93.90%				
[11]	Sum-Rule	98.00%				
	Interpolation 13					
[22]	curve[et transform	97.50%				
	15					
Proposed		99.32%				
Ubiris v2						
[24]	Dual-Hahn	97.5				
	moments 5					
[24]	Krawtchouk	94.5				
	moments 5					
[40]	fuzzy matching	97.11				
[31]	MiCoRe-Net 7	96.12%				
[20]	k-NN 8	94.8				
Proposed	K THI U	98.20%				
Tuposed		20.2770				

Conflict of Interest: The author declares that he has no conflict of interest.

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