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An Efficient Iris Segmentation Algorithm Using Deep Learning Techniques

Sateesh Yaduwanshi, HOD Aditi Khemariya
CSE, MIST Indore
Malwa Institute of Science and Technology
Email - sateeshyadv1@gmail.com

Abstract- The iris segmentation algorithm is very essential in an absolute iris recognition system and has a direct influence on the verification and recognition results of the iris. However, traditional iris segmentation algorithms have poor adaptability and are not robust enough when used in noisy iris databases captured under infinite conditions. In addition, there is currently no large iris database. Therefore, the iris distribution algorithm cannot increase the benefits from the convolution neural network (CNN). Iris segmentation is a basic process of iris recognition. Iris segmentation plays an important role in maintaining the accuracy of the iris by limiting the current defects in the reorganization system. Under these no-ideal conditions, existing segmentation based on local operations cannot see the true iris boundary, and iris segmentation will result in failure. Iris recognition is a significant issue in system control in computer based communication. Human iris recognition is an important branch of biometric verification and has been widely used in many applications, such as attendance maintaining, video monitor system, human - computer interaction, and door control system and network security. This process develops iris recognition to address this problem and introduces a new algorithm using the feature extractions then the classification using vgg16 to significantly improve iris recognition. The execution has performed on the MATLAB software and the performance results carried out in terms of accuracy ,precision and recall,F1.

Key words -Iris segmentation, iris localization,, iris recognition.vgg16,.

I. INTRODUCTION

Image segmentation is an important part of image processing. Depending on the texture, grayscale, color, and shape, it can be split into multiple areas with unique attributes, and then split into areas of interest for further image processing. Image segmentation is a key step from image processing to image analysis. With the rapid development of computer and network communication technologies and the popularization of Big Data, more and more activities related to identity authentication involve the daily life and work of people, such as website login, electronic commerce, banking and presence systems.

Identity authentication consists of confirming the uniqueness and legitimacy of a personal identity through a series of methods. Traditional authentication methods include token-based authentication systems (such as ID cards, passports, driver's licenses) and knowledge-based authentication systems (such as various passwords account or personal identification numbers). Nowadays, with the rapid development of network communication technologies, traditional authentication methods have many drawbacks such as easy to lose, easy to forget, easy to steal, spoof, etc., and it is difficult to respond to the growing demand for information security. Hence, biometric authentication technology has emerged.

Because biometrics is unique and unchanged for individuals, and there are no loopholes such as loss or theft, biometric authentication systems are more reliable and convenient than traditional authentication methods, and have great development potential. The iris has the advantages of uniqueness, immutability and ease of collection [1] Identification of the iris is playing an increasingly important role in the field of biometrics. Iris recognition is considered one of the recognition tools of the human body due to its uniqueness and stability, attracting the attention of more and more researchers. Extracting the features of the iris primarily depends on the ability to accurately position and segment the iris.

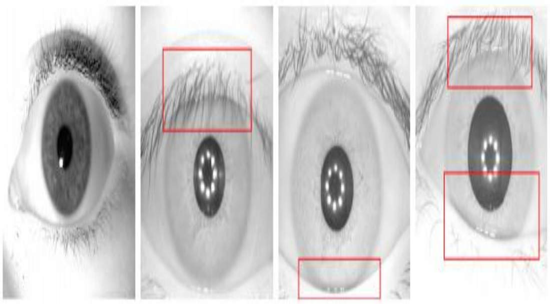

Figure 1. Schematic of iris type. (a) Ideal iris image; (b) the upper eyelid obscures the image (c) Lower eyelids

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block the image (d) Upper and lower eyelids block images.
Biometric recognition plays an important role in identifying a person based on their physiological and behavioral characteristics [1]. There are many biological characteristics that can be used in different applications for different purposes. Each biological characteristic has its own weaknesses and advantages, but the choice of these biological characteristics depends on the different objectives of the application. No specific biological characteristic can successfully meet the requirements of all applications. Although among various biological characteristics, the iris is unique to each person, and compared to other biological characteristics, the iris shows more recognition patterns and the recognition system has excellent performance [2].

Its unique characteristics, stable, contactless and forged. A complete iris recognition system typically includes the following steps: Initially, the iris image is obtained by imaging equipment. Next, an iris segmentation algorithm is used to locate the iris area of the eye image. Then, the iris function is extracted by the feature extraction algorithm. Finally, the extracted iris features are used for iris verification or recognition. Most iris recognition systems include five basic steps: iris image acquisition, preprocessing, iris boundary segmentation, iris feature extraction, and iris feature extraction. Verification or recognition of iris match. In the process of iris recognition, it is very important to accurately segment the iris. By selecting the right iris area, we can extract valuable information from the iris image and further improve the accuracy of the iris recognition system.

This article proposes an automatic iris segmentation method based on the GLCM and VGG 16 algorithm and a convolutional architecture for the classification. This method uses images from popular datasets for training and testing. It is verified that our network model can achieve high precision of iris segmentation in four datasets. Our main innovations and contributions are as follows: Four new workable network solutions are offered, and the best VGG 16 and VGG 19 network models are achieved through training and testing on the same data set. This article provides a method for automatic iris segmentation based on GLCM, which uses popular datasets for training and testing. It is verified that our network model can achieve high precision of iris segmentation in four datasets.

Our main innovations and contributions are as follows: 1) Propose a new network model combined with convolution for the segmentation of iris images. More information about the characteristics of the image can be extracted and the precision of the segmentation can be improved. In order to train and evaluate the proposed model, we collected three challenging public iris datasets: Databases We used the following three representative and publicly accessible databases for experiments.

II.RELATED WORK

Our method is based on the latest CNN architecture for image classification [3] and learning. First, it is transferred from a set of recognized vision tasks and then performs detection and segmentation as in [4]. We reconstruct and perfect the classification network in direct prediction. We map the FCN space and connect the previous model for segmentation and use methods for extracting multi-scale functions to extract functions for recognition.

Convolution Neural Networks (CNNs) CNN is also called multilayer neural network and is used mainly for pattern recognition tasks [5]. CNN can improve the algorithm's resilience to low input changes. By introducing the connection between entanglement and aggregation layers (pools), the proposed architecture is based on different deep neural networks. These DNNs basically belong to different categories of models, which are inspired by Hubel and Wiesel's work with the main visual cortex of cats [6]. The beginning of the architecture, which consists of a series of folding and aggregation layers, is dedicated to automatic extraction of functions, while the other part, which consists of fully connected neuron layers, is dedicated to classification.

The N-fold cards (j∈ {1, ..., N}) in the folding layer Mij parameterize the folded layer Ci (network layer i), Kx × Ky represents the size of the folding core (usually square)), and the connection scheme with the top layer is represented by Li-1. Each folding card Mi j is the result of the sum of the cards of the previous layer Mi-1 j through its respective folding cores. Then add a bias b i j and send the result to the non-linear transfer function Φ (x) [7]. In this case, the graph of the fully connected layer can be calculated as follows.

$$\mathbf{M_J{}^I = \Phi(b_j{}^i + \sum_{n=1}^{N} M_j{}^{i\text{-}1} * K_n{}^i}$$
Where ∗ denotes the convolution operator

Transfer Learning: Transfer learning [8] is a strategy designed to optimize the performance of a learning machine through knowledge and other tasks performed by other learning machines. In practice, according to [9] it is not recommended to train (initialize) the ConvNet model from the beginning, because training the ConvNet model requires a lot of data and takes a lot of time. On the other hand, it is more common to use a trained ConvNet model and solve the problem. This is called transfer learning, which is about transferring learning from one model to another type of problem. There are two types of transfer learning:
VGG: is the runner-up of ILSVRC 2014, [10] used smaller filter 3 × 3 in each convolution layer for the performance improvement. Different versions of VGG

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have been introduced from the last 5 years but the 2 most popular are: VGG16 which contains 16 and 19 layers respectively. Here, CNN Features are generated for the iris recognition task by extracting 2 fully connected layers and outputs of the 16 convolution layers.

Very deep convolution network (VGG):- This model is proposed by [11]. During training, the input to this model is a fixed size 224 × 224 three-channel image. The images are passed through a stack of convolutional (Conv) layers, where small receptive filters of size 3 ×3 (which is the smallest size to capture the notion of left/right, up/down, center) are used. Further 1 × 1 convolution filters are also utilized where a linear transformation of input channels followed by non-linearity is used. To preserve the spatial resolution after convolution, the padding of 1 pixel for 3×3 Conv. layers is employed. Max-pooling over 2×2 pixel window is performed with stride 2.

With different depth in different architectures, a stack of Conv layers followed by three fully-connected (FC) layers have been utilized such as the first two FC layers have 4096 channels and the third FC layer has 1000 channels. The third FC layer performs the Image Net Large Scale Visual Recognition Challenge (ILSVRC) classification. The final layer of this model is the soft-max layer. In all the architectures of this model, the FC layers are the same. Here VGG16 CNN architecture has been employed. Fig. 2 shows the configuration layers of the VGG16 network

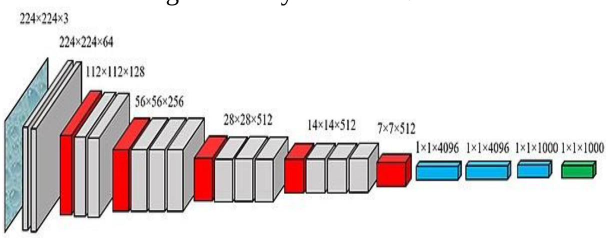

Fig. 2 VGG 16 Architecture.

III. PROPOSED SYSTEM

Iris images were trained by extracting the GLCM and Vgg16 feature from the texture feature of the images. The input Iris image is first preprocessed from the dataset images by using the RGB to gray. The Iris is detecting in the input image and then the features are extracted. Then GLCM and Vgg16 feature were extracted from the image. Then the feature vector is generated. These are considering as test feature. The extracted features were then classified using Support Vector Machine classifier and the Iris is matched. The performance of the process is measured. The process continues till the end. At each node level the generated values were saved as features. The obtained features were used for the classification of the Iris image. The values of the texture were taken as features. The extracted features were then classified using VGG16 network and classifier and the race, liveliness was detected and the Iris is matched. The extracted feature values were then classified based on the label given by the user. The classifier gives the label to which the input image belongs. Three different labels were given in order to find the liveliness, Race and matching of iris. The input image is classified to any one of the two categories that we have specified (i.e.) fake or Real, Asian or Non-Asian. The category of the Iris is also identified using Multi VGG16. It categorizes the images into more number of categories. The performance of our process is measured by calculating the accuracy, sensitivity and specificity of the classifier for the three processes. The accuracy of the classifier represents to which extend the classifier classifies the images based on the given label. The sensitivity of the classifier represents how exactly the classifier correctly classifies the data to each category.The specificity of the classifier represents how exactly the classifier correctly rejects the data to each category.

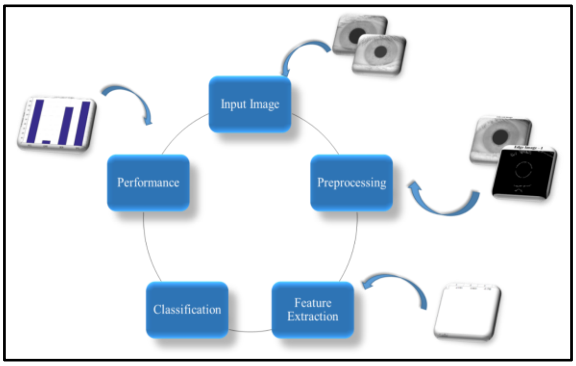

Fig. 3 execution block diagram.

Preprocessing- The acquisition of the eyeball images suffers from various noise artifacts and it is due to the variations in imperfect data acquisition conditions. These noises result from varieties in image quality that leads to inaccurate segmentation of the iris portion within a real-time situation. The accurate iris localization plays a vital role during iris recognition and this iris localization is the process of segmenting an annular iris portion from an eyeball image E. The iris normalization is the process of transforming the localized iris portion into a rectangular array of a given size. The combined process of iris localization and normalization is iris preprocessing.

Segmentation- The most important work in every iris verification system is properly detecting inner and outer boundaries of iris and pupil. For detection of inner and outer boundaries of iris and pupil.

Feature Extraction -In this section, the significant texture features are extracted from the normalized iris. These features will be encoded to create a template. The feature is a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it calculates some significant characteristics of the object. Features such as shape, histogram, texture, color, etc. are useful to describe the

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content of the image. The GLCM methods are used for the feature extraction

GLCM- Quantize the image data. Each sample on the echogram is treated as a single image pixel and the value of the sample is the intensity of that pixel. These intensities are then further quantized into a specified number of discrete gray levels as specified under quantization Create the GLCM. It will be a square matrix *N* x *N* in size where *N* is the **number of level** specified under quantization **.**The matrix is created as follows: Let *s* be the sample under consideration for the calculation.

IV. EXPERIMENTAL SETUP

The model architecture has been implemented at MATLAB 2019b. In VGG16 were trained and tested on three different data sets to prove that the VGG16 models have better performance in iris segmentation. Figure 4 shows the results of VGG16 iris segmentation on three data sets.

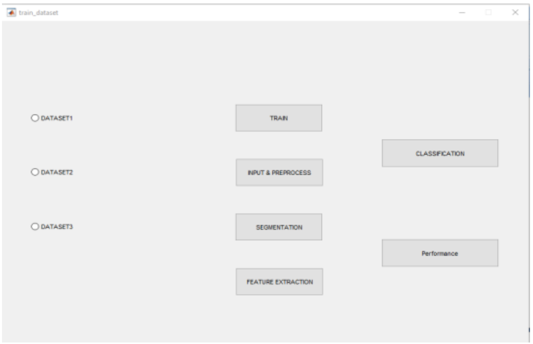

Fig 4 GUI window.

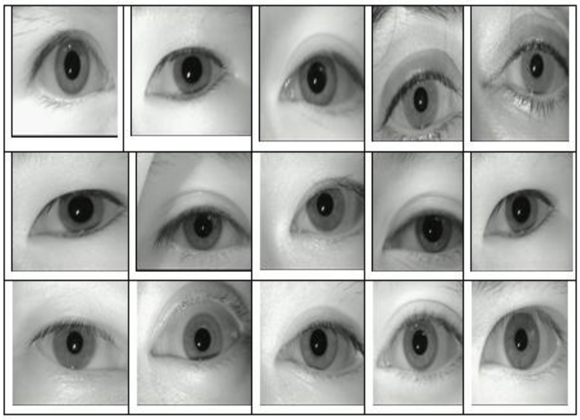

Fig 5 Input data set.

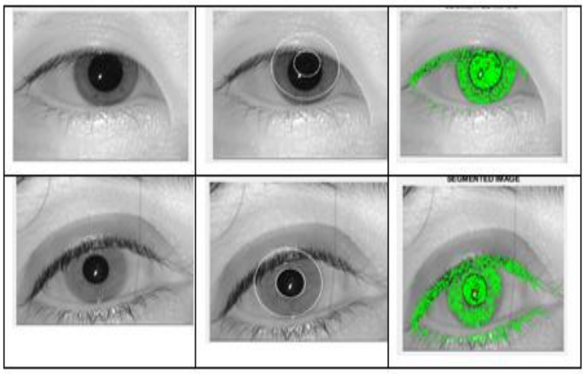

Fig 6 Samples of incorrect segmentation results using the proposed.

There are some incorrectly segmented samples with our method, as shown in Figure 4.4 . Specifically for the first row, the false positive error is mainly caused by reflection noise whose pixel value corresponds to the iris area. For the second line, the defect is mainly in the pupil area, showing a clear discrepancy between the pupil color and the iris image of the training set. In the last line, the dark iris will negatively affect the contrast of the iris pupil and make the iris and pupil pixel difficult to distinguish, resulting in poor segmentation of the iris and pupil mask. In summary, these errors can be caused by the lack of adequate training examples. Therefore, if more noticed training images are given with similar appearance, the segmentation performance is expected to be significantly improved. In addition to evaluation in database, we also performed tests across databases to check the generalize ability of the proposed method. For this we have chosen three other iris databases.

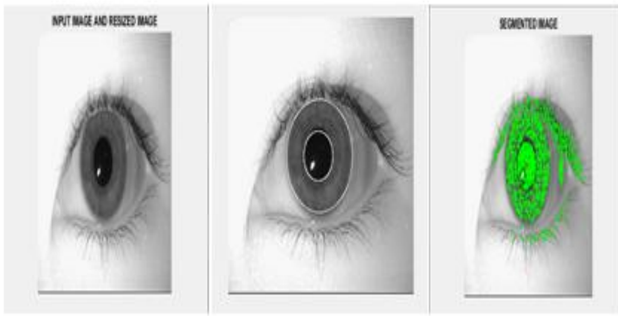

Fig.7 Accurate Detection of Iris and Pupil Boundaries

Testing strategy The proposed VGG16 have been trained in the images of the dataset, but they have been successfully tested on several other iris datasets with good performance. This also enhances the excellent generality of the proposed network. Therefore, the test kit includes the remaining.UBIris-V2 images and several other public data sets. Similarly, we have manually converted (rotated, contrast, and blurred) images to test the robustness of the proposed network during this challenge.

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V.PERFORMANCE MEASURES

System performance is measured by calculating the accuracy, sensitivity and specificity of the classifier. The accuracy of the classifier indicates the area where the classifier ranks the image based on the specified label. Classification sensitivity indicates how the classifier correctly ranks the data in each category. The classifier's specificity indicates how the classifier correctly rejects each data category.

Performance parameters: We have used three parameters accuracy, precision ,sensitivity ,specificity Precision, Recall,

TN- is total number of poorly classified prospects (true negative numbers).

FN- is total number of false rejections, which represents the number of false pixels of foreground pixels classified as background (false negatives).

FP- is total number of false positives, which means that pixels are mistakenly classified as foreground (false positives). Calculate presentation value for each frame of input video based on overhead indicators.

Accuracy: Precision is an indicator for evaluating classification models. Informally, precision is part of the correct prediction of our model. Formally, precision has the following definition:

Accuracy = correct number of predictions, total number of predictions For binary classification, precision can also be calculated according to positive and negative, as follows:

Accuracy = TP + TN+TP + TN + FP + FN

Where TP = true positive, TN = true negative, FP = false positive, FN = false negative

Specificity: Specificity is distinct as proportion of definite refusals that can be predicted as negatives (or true negatives). This means that there is another part of the actual negative number, which is projected as a confident number, which can be called a false positive

Specificity = (True negative) / (True negative + False positive)

The following are true negative and false positive details used in the formula above. True negative = people who are expected to have no disease (or health) do not actually have disease (health); in other words, a true negative signifies number of people who are healthy or predicted to be healthy.

Table 1 Comparison Result with Existing Work

Data base		Approach	Accuracy (%)
Casia-Interval	Existing	Svm	74
	Proposed	VGG16	99.91

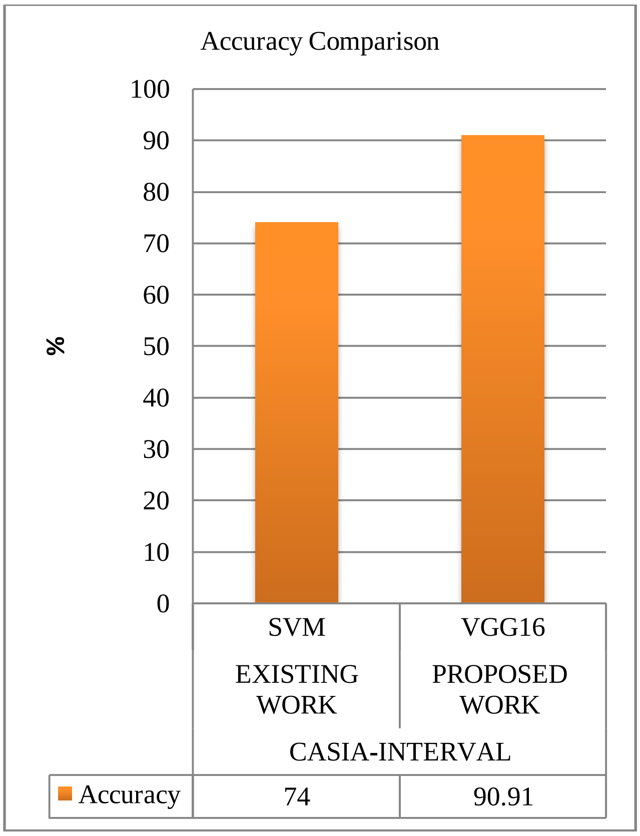

Fig.8 Comparison Result with Existing Work

Table 2 Performance of VGG16 model

Database	Approach	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	Specificity (%)
Casia-Interval	VGG16	99.12	94.44	94.0	0.8949	99.38
Ubris.V2		98.25	99.99	99.95	99.15	99.39
Mmu Database		99.15	99.26	99.12	99.15	99.00

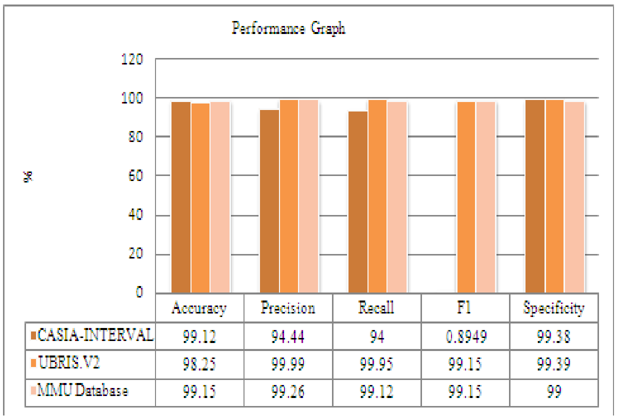

Fig. 8 performance graph.

V.CONCLUSION

The proposed system recognizes the iris of the persons in the dataset based on the features extracted using GLCM and Vgg16 The extracted features are based on the GLCM and Vgg16 which is combined with many of the other texture generation process so that the feature extraction process is more effective. The recognition of the iris is done using the kernel function of the VGG16 classifier. The proposed system gives accuracy which is higher than the existing algorithms which identifies that the misclassifications are reduced to a greater extend. The Texture method used are thoroughly evaluated and shown to significantly outperform the Texture-based counterparts used for recognizing iris on a number of challenging datasets. The proposed method recognize the iris of the person in the video based on the features extracted exactly even if there were numerous challenges such as illumination variations, Contrast variations and the proposed system detects the liveliness and also it detects the race of the person almost exactly in all the cases. The proposed system is not a completely automated system in order to enhance the system can be automated by avoiding a supervised classifiers.

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