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An Efficient Automated Iris Recognition Classification Model Based on Different Convolutional Neural Networks and Transfer Learning.

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KEYWORDS:
Iris recognition, deep learning, Iris Net, Vgg-19 and Inception-V3, CNN.

Abstract— Iris ***is a common biometric used for identity verification. Iris identification is one of the best ways to give people individual authentication based on their iris anatomy. This paper's main objective is to evaluate how well these deep learning networks perform on iris image datasets. The image goes through the following stages: improving image quality; employing the Hough transform and the integro-differential operator to segment the iris; and reducing processing time by changing the image's 150x300 dimensions from Cartesian to polar coordinates. Transfer learning is used to implement the iris classification on three deep learning networks: VGG19, InceptionV3, and Iris Net. The recommended study presents several parameters, including the accuracy of each deep learning network, that were used to create an effective automated iris recognition classification model. For the iris recognition challenge, the study also compares the system's identification ability with several CNN models to determine the optimum outcome. The proposed iris recognition system is tested using Utiris-V1, CASIA Iris Twins-V3, and CASIA-Iris-V3 Interval. The system produced excellent outcomes with a high accuracy rate. Results of the proposed system show that Vgg-19 performs best,*** with ***an overall database accuracy of 1.0 and a per-person recognition time of under one second.***

I. INTRODUCTION

By identifying persons based on psychological or physiological features, biometrics provides a safe and trustworthy identification approach for systems that grant restricted access to physical assets [1]. Iris is considered the most trustworthy biometric technology when compared to other biometrics like face, speech recognition, and fingerprint [2]. The biometric identification process of iris recognition is quick and precise. The iris, a small component in the eye, has several characteristics that make it a strong candidate for biometric identification [3]. Figure 1 depicts the iris, which is the region between the sclera and the pupil. From birth to death, the human iris remains constant and unchanging. Iris is a good biometric for identifying people since it is very

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exclusive, consistent, and the features of the right and left eyes are different [4]. Applications for iris recognition devices range from basic user access control to secure financial transfers, internet access, credit card authentication, and secure banking [5].

The iris recognition system is divided into several steps. The needed region of the iris is first segmented, then adjusted to produce a polar coordinates-based fixed pattern. The features that were extracted from that pattern must then be recognized in the final stage [6]. In many objects identification and computer vision tasks, extracting useful features is a critical step. As a result, many academics have focused on creating reliable features for a range of image classification applications [7].

In 1993, Daugman proposed the first iris identification system, which extracted the binary phase encoding components of an iris image from many orientations and Hamming distance matching using a multiscale 2D-Gabor filter [8]. After decades of comparative research, numerous iris recognition methods have been developed to increase accuracy and usability [9-12]. Feature learning methods and Convolutional Neural Networks are receiving a lot of attention these days (CCN). In this method, the image is immediately entered into the convolutional neural networks. Which subsequently extracts the best aspects of the image [13]. The findings in clearly imply that in most visual identification tasks, characteristics acquired via deep learning with CNN must be used [14].

This work introduces an iris identification model that makes use of transfer learning and a pre-trained convolutional neural network (VGG-19[15], inception-v3[16], and iris-net [17]). In The following is a list of the study's contributions: 1- In the process of transfer learning, the "knowledge" is transmitted from a CCN model trained on one task to another [18]. When there isn't enough data to train a big network from scratch, the transfer learning method is used to avoid overfitting [19]. Additionally, transfer learning saves computing resources, as training from start can take days to weeks [20].

2- Pre-processing processes such as data downsizing, median Blur, segmentation, and normalization to boost classification performance are implemented.

The remaining portions of the paper are structured as follows: Under Section 2, we discuss several similar works as well as the motives for the proposed research. Section 3 discusses how to put the suggested iris recognition technology into practice. Experimental results for the proposed system are presented in Section 4. Finally, the last section contains findings and recommendations for future research.

II. REVIEW OF RELATED STUDIES

Maryim et al [17] demonstrated the iris recognition system's effective structure and robustness. The system's name is IRIS Net. In the architecture of IRIS Net, features are classified into N classes by a SoftMax layer and extracted by a CNN layer, respectively. The original and normalized picture yields from the IITD VI dataset were 97.32 and 96.43 percent, respectively. However, the provided method was limited to one dataset.

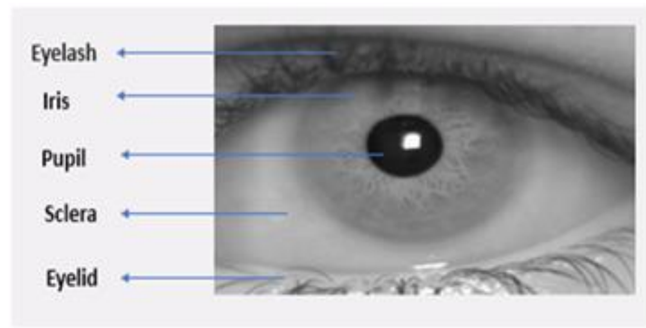

Fig. 1. The outer structure of the human iris

Le-Tien et al [21] explored a modified neural convolutional network (CNN) and a SoftMax classifier-based iris-based biometric system. Thresholding, Hough transform segmentation, and horizontal normalization of the iris segmentation section are all included in the system, providing normalized images with 100 x 100 and 150 × 150-pixel size by histogram equalization. The CNN model is split into two parts, feature extraction and detection, the design created a modified CNN model. The Resnet50 CNN model receives each normalized image and extracts the feature vector from it. The recovered feature vectors are then included in the fully linked layers for training after that, the recovered feature vectors are then applied to the fully connected training layers after that. The proposed method is evaluated using, CASIA Iris Interval-V3 with recognition rate 96.67 %.

Alaslani et al [22] introduced an IRIS Recognition Feature Extraction Using CNN. To categorize the learned features that were taken from a pre-trained CNN, a multiclass Support Vector Machine (SVM) method was employed (Alex-Net Model). On four available datasets, the proposed iris recognition system is evaluated: IITD, CASIA-Iris-V1 and V3 Interval, and CASIA-Iris-thousand. After normalization, the recognition accuracy for iris images was 98.33 % 85 %, 96.6%, and 86.6 % respectively. The outcomes show that the pretrained model's (ALEX- NET) performance has to be improved overall because it performs poorly in some datasets.

Deshpande et al. [23] conducted their experiment using Daugman's integral and differential algorithm. Once the iris border is identified, they adjust the iris to a standard size and encode it in the iris template for matching between the iris templates. The normalization of the iris picture is done with the Rubber Sheet model. In the final matching phase, the iris features are extracted using a 1D logarithmic Gabor filter, where two biometric templates are compared using the Hamming distance as a matching technique for iris verification. Iris images with low contrast or low lighting during detection are one of the hurdles in searching the boundaries; Deshpande's techniques address various issues with non-uniform illumination and reflections. His work enhances the performance of the segmentation and normalization procedure, achieving a 95% overall accuracy and resilient properties in iris authentication systems.

Omran et al [24] provided a comparison of three deep learning models' abilities to recognize iris in noisy environments: Alex net, Vgg16, and Vgg19, as well as a classical method (Masek). The comparison proves that deep learning models are the most effective. CHT accuracy was 68.18 percent for the interval database, whereas three deep learning models had accuracy of 100 percent, 97.88 percent, and 97.5 percent correspondingly for the CASIA Iris Interval-V3, CASIA Iris lamp, and CASIA Iris TWINS datasets. The accuracy of the CHT method was lowered to 4.5 percent at a variance of 0.07, but the accuracies of these models were somewhat reduced to 89.88 percent, 91.54 percent, and 93.61 percent.

Zhao et al. [25] presented a Capsule Network Architecture-based Iris Recognition System. In this study, they developed a capsule network design, Thus, in order to achieve good results, a number of layers of varying depths are built and evaluated on datasets like JluIrisV3.1, JluIrisV4, and CASIA-V4 Lamp. The findings of this study demonstrate that the recommended strategy produces great results. However, because the complexion in this research is too high, the proposed approach may fail on larger datasets.

Thakkar et al [26] presented a computationally intelligent system that could teach itself. The author of this paper employed Gabor channels to derive the highlight vector from the iris highlights. Here, testing using a pre-built neural network is introduced. The authors of this work were employing a controlled neural organization, which was trained with input from many iris include vectors before recognition was directed. In order to find the sweep's centroid inside the pupil's iris, we first had to find the edge image inside the reduced level iris image and then the Hough change within the edge image. The most influential pixel is located in the pupil's mid-inner circle. By removing the unnecessary elements, the iris ring can be removed from the image. At that time, the map framed the iris ring into a 64x512 pixel square. Finally, a low-pass Gaussian channel was deployed to silence the crowd. It's full of repetitions. "Normalize" is the name of this loop. Twenty Gabor channels were obtained, and then all channels were applied to eight image segments to provide a total of 160 segmented images. From these highlights, the average absolute deviation (AAD) was calculated. The AAD values are used to create a cluster of 160 by 1 elements in a single dimension. The enhanced neural network used this one-dimensional cluster to determine whether a user was a verified customer. If they were, the network would return the user's file number as the result. The suggested computation disentangled iris data into expansive and limited categories. Results from putting this formula into practice demonstrated that it is possible to positively identify people by analyzing their irises. This technique employs CASIA-Iris-V3 Interval, which have a success rate of 99%.

Kranthi et al [27] developed a biometric authentication method based on the iris. When it comes to biometric identification methods, the iris is both the safest and most distinguishing option. In this study, the authors provide a modified Hough Transform and use the weightless Mini-VGG Net model to train a network to discover the most effective representations of features. They achieved an impressive 98% accuracy, 0.99 precision and 0.99 recall while classifying data using neural networks. They used CASIA-Iris-V3 Interval, each of which measured 280 by 320 pixels in size, and organized them into 108 folders.

Therar et al [28] proposed a deep learning-based technique using the right of the same individual and left irises to build a reliable multimodal biometric system for identifying the person. To achieve iris recognition, the system includes segmentation (using the CHT algorithm to identify iris area), the rubber sheet model is used to normalize the picture, and the convolutional neural network (CNN) with transfer learning is used to generate specific features that are fed to a multi class SVM algorithm throughout the feature extraction and classification stages. The system's efficiency is tested using two publicly available datasets obtained under varied conditions: CASIA-Iris-V3 Interval and IITD. After training, the implemented system obtains accuracy of 94% and 93% for the left and right iris for the CASIA-iris-V3 interval datasets, respectively, and accuracy of 99% for both the left and right IITD iris datasets.

Rahmatallah et al [29] proposed a hybrid method for enhancing iris recognition accuracy. The suggested iris recognition system entails identifying edges, segmenting the iris, extracting features, and classifying the data. To improve the precision of Iris Recognition, we employ Canny Edge Detection for edge detection, Hough transform for segmentation in order to pinpoint the iris, and then CNN with HD (Hamming Distance) for feature extraction and classification. This model is based on greyscale images from the CASIA-Iris-Interval, IITDelhi, and MMU datasets. When HD was used on CASIA, CNN was used on IITD, and CNN was used on MMU, the recognition rates were 94.88%, 96.56%, and 98.01%, respectively.

We may infer from the aforementioned review that only a small number of authors worked on conventional segmentation algorithms without any alterations, leading to reduced accuracy, and that iris pre-processing is regarded as one of the most important phases for an efficient system. Additionally, it's obvious that many authors examined or tested their method on a variety of databases, which led to improved accuracy on only some of them rather than all of them. Additionally, a few authors have worked on traditional categorization techniques, which have resulted in a loss of accuracy. With rising security standards, accuracy and liveliness detection are becoming increasingly important in today's society. Therefore, it is now necessary to accomplish the objectives by adding transfer learning and pre-trained models that produce better results in less time.

III. THE PROPOSED SYSTEM

The development of the proposed iris recognition system covers the pre-processing stage, feature extraction stage, and classification stage. Convolutional neural networks are used in Figure 2 to represent the suggested iris identification system (Vgg-19, Inception-v3, and iris-net).

A. Image Acquisition

The initial step in iris recognition is picture acquisition, which involves employing cameras and sensors to capture a series of high-quality iris images from the subject. These images should display the complete eye, particularly the iris and pupil, and then some preprocessing may be used to improve the image quality, such as obtaining images with sufficient resolution and sharpness. In most cases, pre-captured images are used to complete this stage. For the recognition, the CASIA database -V3and UTIRIS-V1 were used.

B. Image Preprocessing

The next step is to pre-process the eye image after it has been captured or loaded. Preprocessing images improves the machine's capacity to detect features and objects. Morphological treatments are carried out by preprocessing the image with median blur filtering and cropping high values. It has shown to be very effective in lowering image noise and detail for a variety of computer vision and computer graphics challenges. In computer vision techniques, Gaussian smoothing is additionally applied as a pre-processing step to enhance various sized visual structures [30].

C. Iris Segmentation

Iris segmentation is the next step in iris recognition, and it is a procedure that isolates the actual iris region in a digitized eye image [31-32]. We demonstrate a detection method that combines the Hough Transform and integro-differential operators [33]. All of the necessary stages for iris segmentation and normalization are listed in Algorithm.

1) Hough transform

For detecting the pupil's boundaries, the circular Hough transform is used, this first creates an edge map using Canny Edge detection [34]. Canny Edge Detection has five steps: smoothing, gradient finding, non-maximum suppression, double thresholding, and edge tracking through hysteresis [35].

2) Integro-differential operator

The iris segmentation approach developed by Daugman et al. employing the integro-differential operator is well-studied and well-known. It's a circular edge detector that detects the iris's outside edge. The margins of the elliptical eyelids can also be defined by it. An integro-differential operator's expression is givenbyEq.1:

$$max_{(r,x_0,y_0)} \left| G_6(r) * \frac{\partial}{\partial r} \int \frac{I(\times,y)}{2\pi r} ds \right| \quad (1)$$

Where I (x, y) denotes a circle's representation of an eye, where the search radius is r, and the smoothing function G(r) has the factor r. With a maximum gradient change, the center coordinates (x0, y0), and a circular arc of radius r, this operator scans a circle input image.

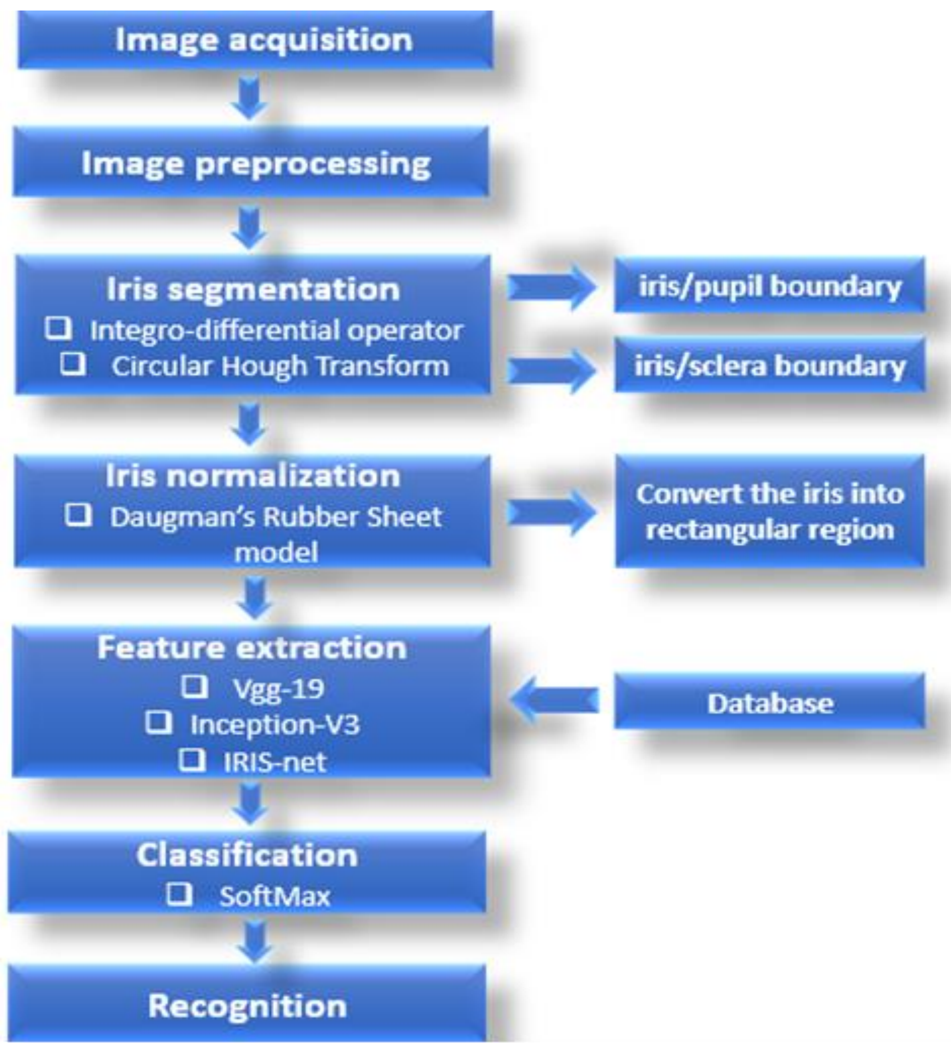

Fig. 2. Proposed Iris Recognition System

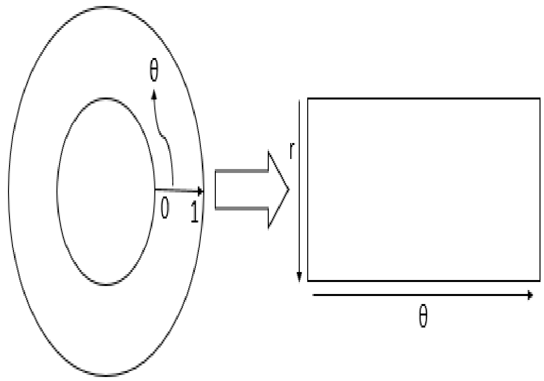

Fig. 3. Rubber sheet model by Daugman

D. *Iris Normalization*

After the iris region has been identified through the iris' inner and outer boundaries (information components outside of this region are eliminated), normalization is employed to create an image with a standard size [36]. The iris normalization process makes use of the rubber sheet concept. The localized iris area in Figure 3 shows how each pixel is remapped from Cartesian (x, y) to Polar (r, θ) coordinates. Where r stands for the [0, 1] range and (θ) for the [0,2π] angle. The area of the iris can be mapped to normalized polar coordinates as in (2, 3, 4)

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

Where

$$x(r,\theta) = (1-r) \times xp(\theta) + xi(\theta) \quad (3)$$

$$y(r,\theta) = (1-r) \times yp(\theta) + yi(\theta) \quad (4)$$

Where;

Where I (x, y) stands for the iris region, The primary Cartesian coordinates are (x, y), the polar conformable coordinates are represented as (r, θ), and xp,yp &xi,yi stand for the coordinates of the pupil & iris region along the direction [37]. Figure.4 shows the final results from the segmentation and normalization processes.

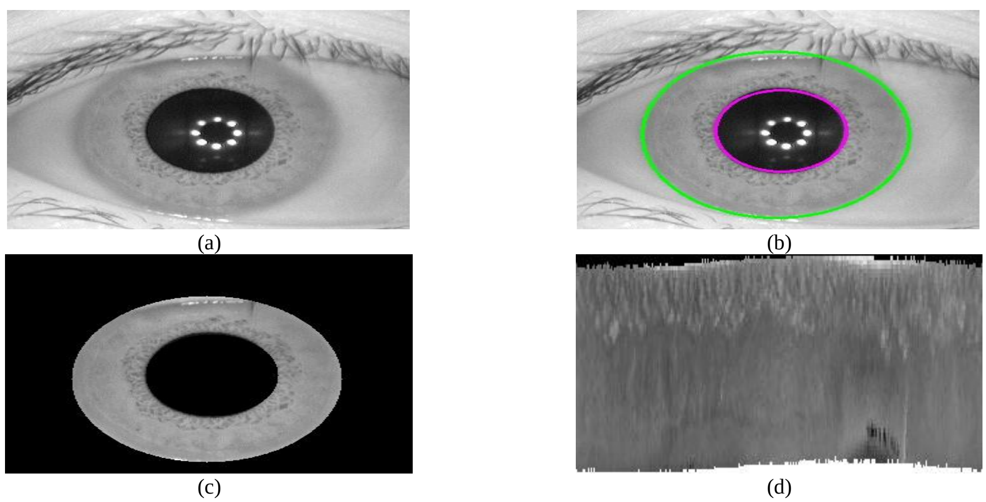

Fig4. Results of the CASIA iris interval segmentation and normalisation for (Image 01-R) (a) Original input image. (b) Iris-to-pupil border detected. (c) Segmented image of the iris. (d) A normalized image of the iris.

Algorithm 1: Automatic segmenting and normalizing of the iris.

Input: Eye image.
Output: The iris's center and radius, the pupil's center and radius, and the iris's straightened image.

1 Define the radius ranges for the pupil and iris, and manually adjust the radius ranges using the database.
2 Pre-processes the image
- Crops high values of the image.
- Apply median Blur.

3 Find the pupil center using a naive method
4 Find the pupil using Hough transform
- Create an edge map using canny edge detection.
  a) Use a Gaussian filter
  b) Use a gamma function
  c) Use non-maximum suppression.
  d) Use the hysteresis thresholding method.
- Apply circular Hough transform
- For each edge point, draw circles with various radiuses.
- In the Hough space, find the maximum, which will be the circle's parameters.

5 Finds the iris using integro-differential operator
- Perform line integration and carry out the differentiation.
- Determine the coarse center coordinated and radius's maximum value for the blurred image.

6 Return the iris's center and radius, as well as the pupil's circle
7 Using x = r cos and y = r sin, Calculate each data point's Cartesian location around the iris's circle form.
8 Using unravel iris to transform it to a straightened representation.
9 Return straightened image of the iris and store it in polar array.

F. Feature Extraction

With a convolutional neural network model that has already been trained, we use transfer learning in this stage (Vgg-19 model, Inception-V3 model, and the Iris -Net).

1) Vgg-19

The VGG-19 is a more complicated network with 19 convolutional layers. Five fully connected layers, five layers with maximum pooling, and five layers with Relu and dropout are present. VGG-19 divides its convolutional layers into five sets, with a max pooling layer coming after each one. 64 filters comprise the initial set of convolutional filters, and the number of filters rises by a factor of two after each max-pooling layer until the last group has 512 filters. All convolutional layer filters have a size of 3 × 3 by default. The stride and padding of every convolutional layer are also set to 1. With stride 2 max-pooling is done over a 2 x 2 window. In order to classify and extract features, the pre-trained (VGG-19) is fine-tuning. The VGG-19 model, which was initially trained on Image Net, is used for the transfer learning process, and here is the data from predictions by the VGG-19 model are expected. [38].

2) Inception-V3 model

This network is made up of 270 layers and is based on inception modules [39]. Convolutions corresponding to various kernel sizes are used in these inception blocks to abstract characteristics and finally aggregate the findings. Convolution, batch normalization, and Relu are applied to the input image first, then, for feature extraction, pooling and several inception layers are utilized.

3)Iris -Net

There are two completely linked layers, four pooling layers, nine activation Relu layers, and four convolution layers in this model. Finally, the dropout layer is employed in the classification section to lessen overfitting, and the output layers are SoftMax with cross-entropy.

That automatically identifies and extracts characteristics from images without the need for domain expertise. IRIS Net has 18 layers. Convolution is the first layer, followed by Rule, Pooling, and fully-connected (FC) layers, before finishing with the SoftMax layer. Each fully connected layer is followed by two dropout layers to reduce overfitting in fully connected (FC) layers. It stops all neurons from updating their weights at the same time. This layer limits the simultaneous interactions of all neurons with the same target.

4)SoftMax Classifier

The final layer in CNN systems is the SoftMax (VGG-19, Inception-v3and Iris-Net). The SoftMax regression classifier is a multi-class classification task that uses a broad type of binary logistic regression classifier. Suppose there are K classes, and there are n labelled training samples ((x1, y1), (xn,yn)),where (i∈(1,2,…n))is the training data, and (j∈(1,2,…n)) is the class label. If we provide the SoftMax classifier with an input feature input xi, it will produce a K-dimensional vector (whose members add to 1), and each element in the output vector displays the projected probability of each class label given this input feature [40]. Algorithm 2 lists all of the necessary processes for extracting and classifying features employing a convolutional neural network model that has already been trained.

Algorithm 2: Using a pre-trained CNN to extract features and classify them using the SoftMax technique.

Input: The input images
Output: The recognition accuracy

1 Create training and validation image classes from the images.
2 Load pre-trained CNN (Vgg-19, Inception-v3 and Iris Net).
3 Adjust the Pre-trained model: dependent on the number of classes, adjust the final fully linked layer.
4 Pre-process images for the (Vgg-19-Inception-v3 and iris-Net model).
5 Extract features from the model's deeper layers and use the training set to obtain training labels.
6 Utilized the SoftMax Classifier training features.
7 The process of extracting the test set's features.
8 Utilize the learned classifier to make a label prediction for the test set.
9 Obtain the known labels of the test set.
10 Use a confusion matrix to tabulate the results.
11 Convert the confusion matrix to a percentage.
12 Display the mean accuracy.

IV. RESULTS OF EXPERIMENTS AND ANALYSIS

The experimentation results for the proposed algorithms will be discussed in this portion of the article. and compare them to other works.

A. Database

Three commonly used iris datasets are utilized to evaluate the suggested method: CASIA-Iris-Interval-V3 [41], CASIA-Iris-Twins-V3 [42], and UTIRIS-V1 [43]. The database was divided into two sections: design and test (each person is given ten images) 8 Images for design and 2 images for testing). UTIRIS-V1 contained each and every design image used in this experiment. 1729 images in this trial belong to 122 design classes and 688 Images belong to 122 testing classes. In addition, there are Found 456 photographs belonging to 21 classes and Found 337 images belonging to 21 classes for testing in the CASIA iris interval. Found 1087 Images belonging to 100 classes for design and Found 487 images belonging to 100 classes for testing in CASIA iris twins. The most crucial data from these databases is compared in Table 1, including the number of subjects for whom images were captured, the quantity of images in each database, and the format, size, and type of instrument used to take the images.

TABLE.1
THE DETAILS OF THE DATASETS THAT WERE USED.

Features of the subset	CASIA iris interval	CASIA iris twins	UTIRIS-V1
Sensor	CASIA close-up iris camera	OKI IRISPASS-h	ISG Light wise LW
Environment	Indoor	Outdoor	Indoor
Session	Most iris images require two sessions.	One	Two different sessions
characteristics of subjects	The majority are CASIA graduate students.	Most of those taking part are kids in the Beijing Twins Festival.	The majority are University of Tehran Iris graduate students (UTIRIS)
Number of subjects	249	200	79
Number of classes	395	400	158
Number of images	2,639	3,183	1540
Resolution	320*280	640*480	1000x776
Features	Images of the iris from several sessions that clearly show the iris's texture	This is the first twin iris image dataset made available to the public.	Its first iris biometric central database was registered over two separate sessions using near infrared (NIR) and visible wavelength (VW) technology (NIR).

Fig 5. CASIA-Iris-Interval, CASIA-Iris-Twins, and UTIRIS dataset images (first row, second row, and third row, respectively).

B. Experimental settings

In this study, training is carried out on 80% of the randomly selected samples. From the training set of samples, 20% are chosen for validation. To determine the network's ability to set up and retain weights with the fewest possible validation errors, validation collection is used. The selection of the right CNN network design is one of the key components of the training strategy. The goal of the divided design data for training and validation is to set aside a portion of the design data and utilize it to track performance. The tested images were trained using the images from the intended part (D set), which had been completed (T set), which were categorized based on the intended part's training images (D set). The weights are chosen random at the start of CNN training. It does not produce satisfactory outcomes. The goal of deep learning training is to build up from a low-performance network to a neural network with high resolution. After training, the loss function should be as small as possible. The weight is updated using the learning rate. The loss functions are optimized using a variety of techniques. Adam [44] It is among the most straightforward gradient-based techniques. The back propagation algorithm is used for training, and Adam is used for updating the weight [45].

In our experiment, we used a CNN model with proper hyper-parameter tuning, which can achieve high accuracy in shorter epochs of time, with the best accuracy at 100 epochs. The system and phases are implemented using a jupyter notebook (anaconda3) on a laptop with a Core i7-8565u processor and 16 GB of RAM. The hyper parameters settings for the evaluated CNN models are listed in Table.2.

TABLE.2
TRAINING PARAMETERS OF SUGGESTED SYSTEMS

Models	Image Size	Activation	Dropout	Batch Size	Epoch	Learning Rate	Optimizer
Vgg-19	150 × 300 × 3	relu	0.3	32	50-100	0.01	Adam
Inception-V3 model	150 × 300 × 3	relu	0.3	32	100-120	0.01	Adam
Iris -Net	150 × 300 × 3	relu	0.3	32	100	0.01	Adam

C. *Analysis of performance on Proposed Networks*

In this part, the suggested networks' reliability and effectiveness are evaluated. Table .3 displays the experimental outcomes. The Confusion matrix is one of the simplest measures for gauging the consistency and accuracy of the model. It's used to solve categorization difficulties involving two or more distinct types of production groupings. An independent performance indicator is the Confusion Matrix. But it and the values contained inside it are used in practically all performance measurements [46]. The Confusion matrix produced after classification from the model. Every model was assessed using a standard performance evaluation method (Mean Squared Error, Accuracy, Specificity, Precision, Recall, and F Measure).

The metrics offered in Eqs. 3, 4, 5, 6, and 7 are used to evaluate the networks:

$$Accuracy = tp + \frac{tn}{tp} + fp + fn + tn \quad (5)$$

$$Recall = tp/(tp + fn) \quad (6)$$

$$precision = tp/(tp + fp) \quad (7)$$

$$F1score = 2 \times \frac{Recall \times precision}{Recall + precision} \quad (8)$$

$$MSE = 1/n \sum_{i=1}^{n} |Yi - \widehat{Yi}| \quad (9)$$

Where tp, tn, fp, fn, yi, and I represent true positive, true negative, false positive, false negative, and inverted positive, false negative, and reversed positive, respectively. For the ith observation, the observed value and the predicted value [47].

TABLE.3
THE ACCURACY AND THE RESULTS OBTAINED FROM THE CONFUSION MATRIX

Database	Modules	Recognition Accuracy	Precision	Recall	Mean Squared error	F1 Measure	Time (S)
CASIA Iris Interval -V3	VGG-19	1.000	1.000	1.000	0.06	1.000	18s/step
	InceptionV3	1.000	0.99	1.000	0.12	0.994	4s/step
	Iris Net	0.994	1.000	0.99	0.0	0.994	4s/step
CASIA iris Twins- V3	VGG-19	0.985	0.99	0.98	6.02	0.984	22s/step
	InceptionV3	0.983	0.98	0.98	6.82	0.98	4s/step
	Iris Net	0.981	0.98	0.98	9.9	0.98	355ms/step
UTIRIS-V1	VGG-19	1.000	1.000	1.000	0.02	1.000	22s/step
	InceptionV3	0.913	0.90	0.92	15.06	0.909	3s/step
	Iris Net	1.000	1.000	1.000	0.0	1.000	368ms/step

As shown in Table 3, we find that different results were obtained using vgg-19, InceptionV3and Iris Net in CASIA iris Interval -V3, the recognition rate was 100% in using the training model (vgg-19) with 100 epochs, 100% using Inception v3 with 100 epochs, and 99.4% in Iris Net with 100 epochs. The recognition rate was 98.5%, 98.3% and 98.1%respectively for vgg-19, InceptionV3and Iris Net in CASIA iris Twins- V3. As well as in UTIRIS-V1 was 100%, 91.3% and 100%

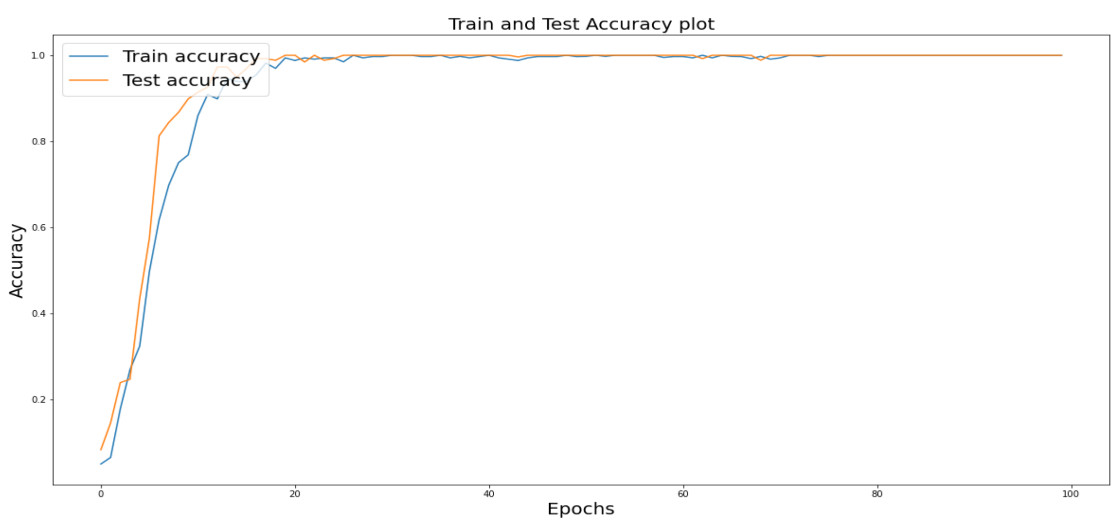

Fig 6. Accuracy over 100 epochs from CASIA Iris Interval (Vgg-19).

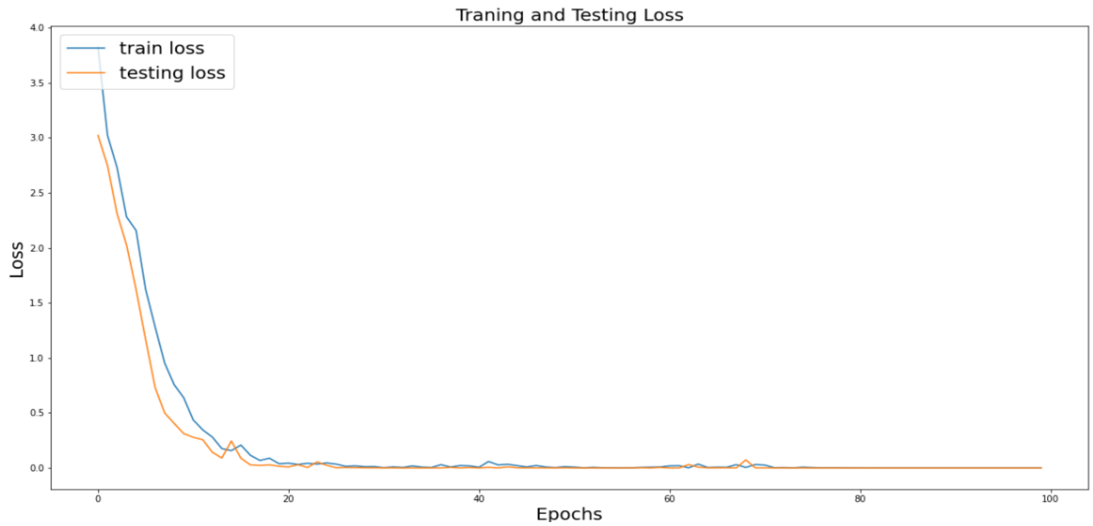

Fig 7. Loss rate over 100 epochs from CASIA Iris Interval (Vgg-19).

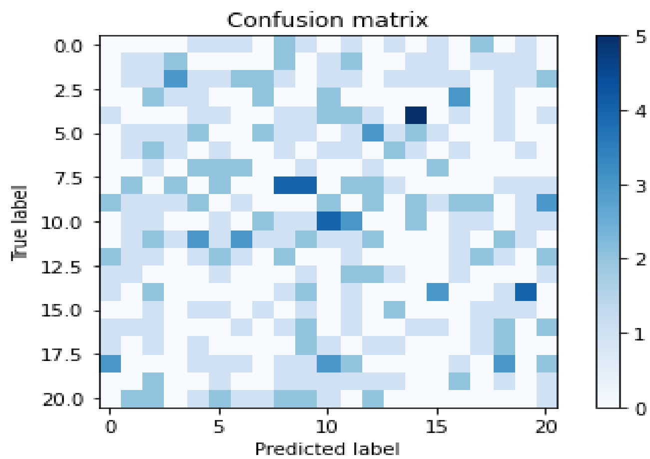

Fig8. CASIA iris interval prediction confusion matrix (Vgg-19)

Figure 6,7 shows the progress of the VGG19 training over 100 epochs in terms of accuracy and error loss. In Fig. 8 and Table 3, the performance of model is illustrated, based on the confusion matrix, with class-specific recall, precision, f1 score, and total accuracy using CASIA iris interval.

Figure 9, 10 depicts the vgg-19 training progresses over 50 epochs with accuracy and error loss. Fig. 10 and Table 3 from the confusion matrix demonstrate the model's performance in terms of class-wise recall, precision, f1 score, and total accuracy using CASIA iris twins.

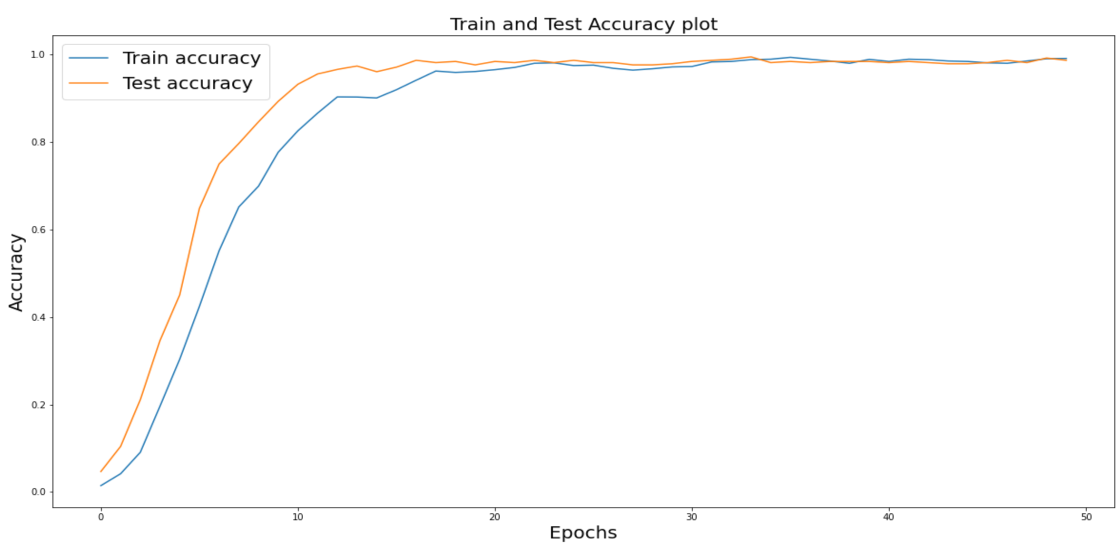

Fig 9. Accuracy over 100 epochs from CASIA Iris Twins (Vgg-19)

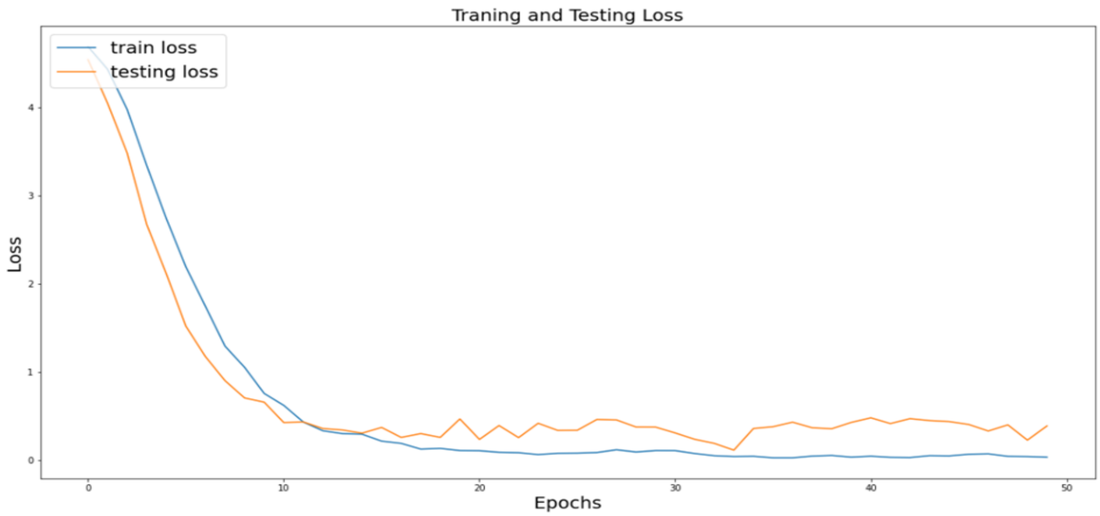

Fig 10. Loss rate over 100 epochs from CASIA Iris Twins (Vgg-19)

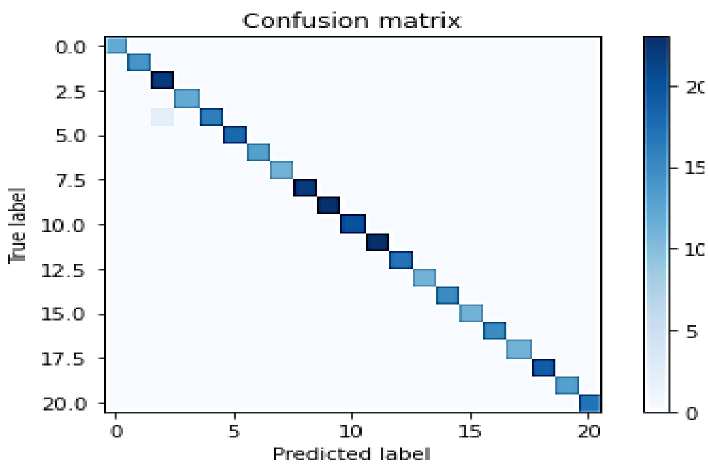

Fig 11. CASIA iris twins prediction confusion matrix (Vgg-19).

Figure 12,13 depicts the vgg-19 training progresses over 100 epochs with accuracy and error loss.Fig. 14 and table.3 from Based on the confusion matrix, UTIRIS displays the performance of the models in terms of class-wise recall, precision, f1 score, and total accuracy.

On the CASIA-Iris Interval, CASIA-Iris Twins, and UTIRIS databases, our proposed model produces the best results. Table.4 shows a performance comparison of the model to the existing model.

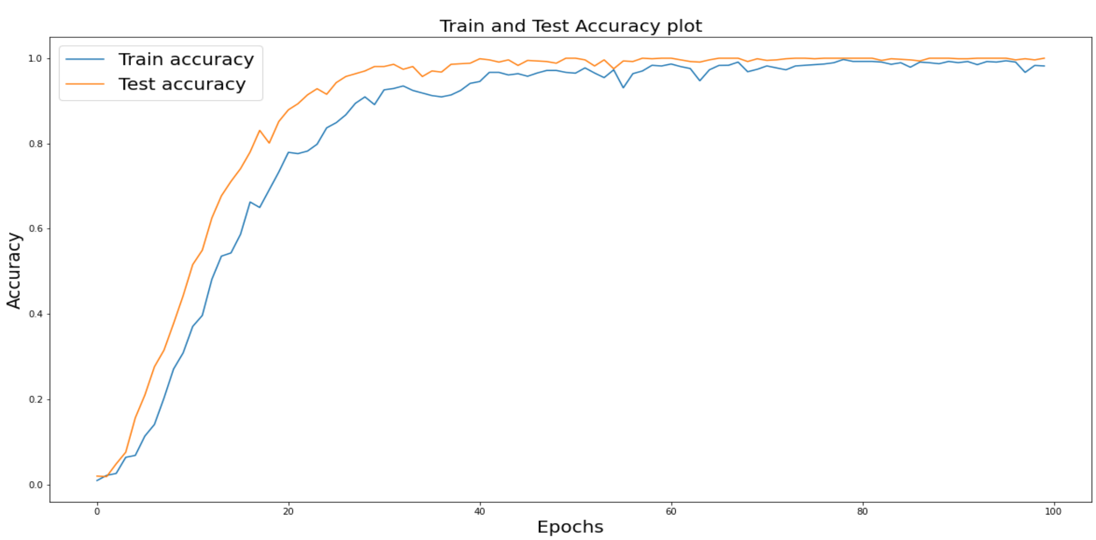

Fig 12. Accuracy over 100 epochs from UTIRIS (Vgg-19).

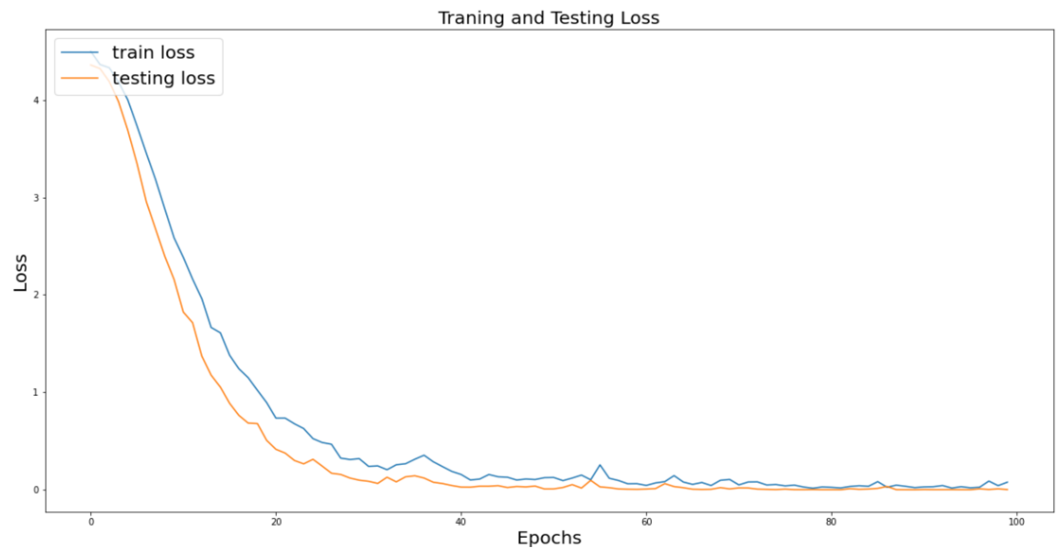

Fig 13. Loss rate over 100 epochs from UTIRIS (Vgg-19).

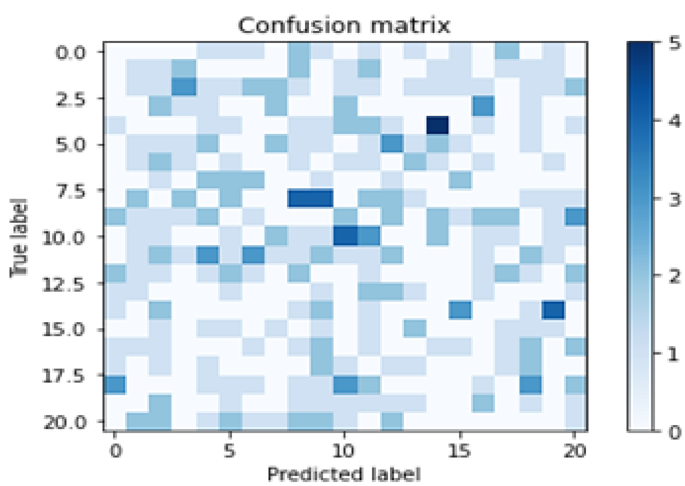

Fig 14. UTIRIS prediction confusion matrix (Vgg-19).

TABLE.4
A COMPARISON OF THE PROPOSED METHOD'S RESULTS ON THE IRIS DATASET USING STATE-OF-THE-ART METHODS.

Reference#	**Feature Extraction**	**Classification**	**Database**	**RecognitionAccuracy**
[21]	IrisConvNet	SoftMax	CASIA-Iris-V3 Interval	96.67 %
[22]	Alex-Net Model	SVM	CASIA-Iris-V3 Interval	86.6%
[23]	1D log-Gabor filter	Hamming distance	UTIRIS V.1	95%
[24]	Alex-net Vgg-16 Vgg-19 Masek	SoftMax	CASIA-Iris-V3 Interval CASIA-Iris-V3 Twins	100% 97.84%
[26]	Gabor filters	supervised neural network	CASIA-Iris-V3 Interval	99%
[27]	Mini-VGG Net	SoftMax	CASIA-Iris-V3 Interval	98%
[28]	CNN	SVM	CASIA-Iris-V3 Interval	The left and right iris scored 94% and 93%, respectively.
[29]	CNN with HD	SVM	CASIA-Iris-V3 Interval	94.88%
Proposed	Vgg-19 Inception-v3 Iris-net	SoftMax	CASIA-Iris-V3 Interval CASIA-Iris-V3 Twins UTIRIS V.1	100% 98.5% 100%

V. CONCLUSION

This paper presents an efficient and effective method for iris-based biometric recognition. The system starts by performing image preprocessing operations like segmentation and normalization to generate a normalized image with dimensions of 150x300 pixels for use as the CNN input image. This study proposed and extracted features using a CNN-based deep learning system with transfer learning and the SoftMax classifier. The system is divided into two sections: one for feature extraction and another for recognition. Extracting features is done using the Vgg-19 model (16 first layers), InceptionV3 (250 first layers), and Iris-net (20 first layers). The suggested system's results demonstrate that Vgg-19 performs best with 1.0, 1.0, 1.0 and 0.06 respectively for accuracy, Precision, recall accuracy and Mean Squared error across CASIA Iris interval-V3, 0.98, 0.99, 0.98, 6.02 across CASIA Iris Twins-V3 and 1.0, 1.0, 1.0, 0.02 across Utiris-V1 and a recognition time of less than one second per person. Training, feature extraction and testing take very little time.

AUTHORS CONTRIBUTION

Contribution	Authors
Conception or design of the work	***Abeer Twakol & Ibrahim Yasser***
Data collection and tools	***Ghada Abd El-Latif***
Data analysis and interpretation	***Ghada Abd El-Latif***
Funding acquisition	***No funding***
Investigation	***Ghada Abd El-Latif***
Methodology	***Mohy Eldin Ahmed***
Project administration	***Abeer Twakol & Ibrahim Yasser***
Resources	***Ghada Abd El-Latif***
Software	***Ghada Abd El-Latif***
Supervision	***Abeer Twakol & Ibrahim Yasser***
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Critical revision of the article	***Abeer Twakol & Ibrahim Yasser***
Final approval of the version to be published	***Abeer Twakol & Ibrahim Yasser***

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Title Arabic

نموذج تصنيف آلي فعال للتعرف على قزحية العين يعتمد على شبكات عصبية تلافيفية مختلفة وتعلم النقل.

Arabic Abstract

القزحية هي مقياس حيوي شائع يستخدم للتحقق من الهوية. واحدة من أكثر الطرق فعالية لتزويد الأفراد بمصادقة فريدة بناءً على بنية IRIS الخاصة بهم هي التعرف على قزحية العين. الهدف الأساسي من هذه الورقة هو تقييم أداء شبكات التعلم العميق هذه على صور القزحية. تمر الصورة بالمراحل التالية: تحسين جودة الصورة ، وتجزئة قزحية العين باستخدام عامل تفاضل متكامل وتحويل Hough الدائري ، وتحويل الصورة من الإحداثيات الديكارتية إلى إحداثيات قطبية لتقليل وقت المعالجة بأبعاد ٣٠٠*١٥٠. تصنيف القزحية على ثلاث شبكات تعلم عميق: VGG19 و InceptionV3 و Iris Net. تعرض الدراسة المقترحة العديد من المعلمات ، بما في ذلك دقة جميع شبكات التعلم العميق الثلاث ، التي تم استخدامها لإنشاء نموذج تصنيف فعال للتعرف على قزحية العين. تقارن الدراسة أيضًا أداء التعرف على النظام مع العديد من نماذج CNN للعثور على أفضل نتيجة لتحدي التعرف على قزحية العين. يتم استخدام Utiris-V1 و CASIA Iris Twins-V3 و CASIA-Iris-V3 Interval لاختبار نظام التعرف على قزحية العين المقترح. مع معدل الدقة العالي ، أنتج النظام نتائج رائعة. توضح نتائج النظام المقترحة أن Vgg-19 يعمل بشكل أفضل مع دقة ١,٠ عبر جميع قواعد البيانات ووقت التعرف أقل من ثانية واحدة لكل شخص .