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A Robust Iris Recognition Approach Based on Transfer Learning

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Abstract: Iris texture is one of the most secure biometric characteristics used for person recognition, where the most significant step in the iris identification process is effective features extraction. Deep Convolutional Neural network models have been achieved massive success in the features extraction field in recent years, but several of these models have tens to hundreds of millions of parameters, which affect the computational time and resources. A lot of systems proposed in the iris recognition field extract features from normalized iris images after applying many pre-processing steps. These steps affect the quality and computational efficiency of these systems; also, occlusion, reflections, blur, and illumination variation affect the quality of features extracted. This paper proposed a new robust approach for iris recognition that locates the iris region based on the YOLOv4-tiny, then it extracts features without using iris images' pre-processing, which is a delicate task. In addition, we have proposed an effective model that accelerated the feature extraction process by reducing the architecture of the Inception-v3 model. The obtained results on four benchmark datasets validate the robustness of our approach, where we achieved average accuracy rates of 99.91%, 99.60%, 99.91%, and 99.19% on the IITD, CASIA-Iris-V1, CASIA-Iris-Interval, and CASIA-Iris-Thousand datasets, respectively.

Keywords: Iris recognition, Deep Learning (DL), Transfer Learning (TL), Convolutional Neural Network (CNN), Pre-trained Inception-v3, YOLOv4-tiny

1. Introduction

Biometric systems have grown rapidly in recent years, where they have been used in many applications such as mobile phones, database access, financial services, access control, and military fields. Users in biometric systems do not need to carry any traditional proofs such as PIN codes, passwords, and ID cards, because these proofs may be stolen or forgotten [1]. Biometric systems have replaced the traditional proofs by physical and behavioral traits of users such as voice, ear, fingerprint, face, hand geometry, iris, and DNA [2]. The human iris texture patterns are universally unique biometric features and invariant for every human over time [3]; they are distinct even between twins [4]. Accordingly, iris recognition is one of the most secure biometric techniques. It was used in many applications requiring high-security levels, such as banking, military fields, and border security control.

Recently, Deep Learning, precisely Convolutional Neural Networks (CNN), has achieved massive success in the Computer Vision field [5], [6]. The iris recognition approaches have benefited from this success, where several methods were proposed based on Deep Learning, such as iris detection [7], iris segmentation [8], [9], feature extraction [10], [11], and iris recognition [12], [13].

Despite the attempts of researchers to use Deep Learning to develop the iris recognition field, these attempts remain few due to the great importance of iris recognition tasks in several fields. The disinterest of researchers in this field is due to the absence of very large databases available for researchers. For achieving good performance with Deep Learning, we need a massive amount of training data. But the largest available iris dataset is the ND-CrossSensor-2012 database [14] which composes only 117,503 images. This number is tiny to train a deep neural network that contains millions of parameters from scratch. To overcome this challenge, researchers applied Data Augmentation (DA) and Transfer Learning (TL) in many previous studies. Data augmentation is a technique applied to increase the amount of the training set by using different transformations such as image rotation, scaling, vertical or horizontal mirroring, zooming, etc. Transfer learning is a machine learning algorithm that uses knowledge learned while solving one task to help another related task [15], where there are two popular methods in transfer learning that have been used in the iris recognition field. The first one has used the off-the-shelf features extracted from one task directly on the iris recognition task without any modification; on the contrary, in the second method, we train the pre-trained model on the new training set (iris images dataset) to fine-tune the

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features to adapt with the new task.

A. Related work

Several approaches have been proposed for iris recognition in recent years. We will focus on some of these approaches in this paper.

Winston and Hemanth [16] proposed two modified Self Organising Map (SOM) used for iris classification. However, the classifier performance did not get a high result, where it achieved a 98.8% accuracy rate on the IITD database. In addition, Dua et al. [17] suggested a system of iris recognition based on the circular Hough transform to segment irises and Daugman's rubber sheet model to create the Rectangular Iris Images. Then they used the Log-Gabor filter to generate a unique iris code. Finally, they used neural network structures for the classification. The proposed system gets an accuracy of 97 % on CASIA-Iris-V1.

Recently in 2022, Abdo et al. [18] proposed an iris recognition system based on the Fuzzy Local Binary Pattern [19] to extract features, in which the FLBP is an extension of the LBP that applies fuzzy logic to build the local patterns. The system used multiple classifiers in the classification task, where the SVM achieved the best accuracies. Khotimah and Juniati [20] proposed a system for iris recognition based on three steps, the first step normalized the iris image into a rectangular block by using the Hough transformation and Daugman's rubber sheet model, the second step extracted the characteristics of the iris based on the box-counting method, and finally used the K-Nearest Neighbor (KNN) for the classification. The proposed system achieves an accuracy rate of 92,63 % on the CASIA-Iris-Interval.

A new technique for iris recognition based on Histogram Equalization and Discrete Cosine Transform (DCT) was proposed. This technique used The Circular Hough Transform algorithm to localize the iris region and then used Daugman's rubber sheet model to normalize iris images. The authors [21] applied Histogram Equalization on the normalized iris image to obtain a well-distributed texture iris image before extracting features by Discrete Cosine Transform (DCT). For the classification task, they used multi-class SVM. They also implemented Discrete Wavelet Transform (DWT) and Local Binary Pattern (LBP) to compare their accuracy to extract features with (DCT). This technique achieved an excellent accuracy rate compared with LBP and DWT, but its accuracy is lower than existing state-of-the-art techniques .

Abdalla et al. [22] extracted the features from the normalized images using a combination of DWT and DCT techniques, then used multi-class SVM for the classification. The proposed approach achieved an accuracy rate of 97 % on the CASIA-Iris-Interval, where 400 iris images are used for training and 300 images used for testing.

Minaee et al. [23] proposed a system for iris recognition by using pre-trained VGG-NET to extract features, and then the authors used the multi-class SVM for classification. The proposed system achieved 99.4% and 90% accuracy rates on the IITD and CASIA-Iris-Thousand datasets, respectively. Alaslani [24] proposed a system for iris recognition that used canny edge detection and circular Hough to segment iris images and the rubber sheet model to normalize them and then extract features from the segmented and normalized images using the pre-trained CNN (AlexNet). The proposed system used the multi-class SVM for classification. This system achieved a high accuracy with the segmented iris images compared to the normalized images. Furthermore, Alaslni et al.[25] proposed an iris recognition system based on transfer learning; the proposed system fine-tuned the pre-trained VGG16 and used them for features extraction and classification. This system tested with four datasets contains just 60 classes in each dataset. The accuracy rate of this system is 95% in the CASIA-Iris-Thousand dataset and 91.6% in CASIA-Iris-Interval datasets.

Arora and Bhatia [26] proposed a Deep Learning approach for iris identification and verification. The authors used the Circular Hough transform to localize the iris in the image. Then they used a proposed deep CNN to extract features from localized iris followed by a Softmax classifier. But only one dataset was used to test this approach. The proposed approach achieves 98% on the IITD database split into training, test, and validation sets (60/20/20%). Yifeng Chen et al. [11] proposed a novel loss function called Tight center, and they tested this loss function with Tiny VGG, MobileNet, and ShuffleNet on three available databases. The proposed method could achieve an excellent accuracy rate on large datasets, but their accuracy degrades on small datasets. In additon, Sujana and Reddy [27] proposed a Convolutional Neural Network (CNN) to extract features from the normalized iris image. The proposed CNN trains from scratch on two different datasets, namely IITD and CASIA-Iris-V1; the suggested model achieves 98.05% and 95.04%, respectively.

Recently in 2022, Shanto et al. [28] proposed an iris segmentation and recognition system. The system used the Circular Hough Transform (CHT) and Canny Edge Detection to segment iris images. In addition, the authors proposed a CNN model to extract features from the segmented images. The proposed model contains three convolution layers, in which a max pooling layer follows each convolution layer. Moreover, for the classification task, the CNN used a flattened layer followed by three layers: dense, dropout, and softmax.

Kranthi Kumar et al. [29] suggested an iris recognition approach based on mini VGG architecture. The deep CNN proposed trains from scratch on the CASIA-Iris-V1 database to extract the best features from the normalized iris images. The proposed approach achieves an accuracy rate of 98%. In 2022, Hassan et al.[30] proposed an iris recognition system based on CNN features. The proposed system used the Circular Hough Transform (CHT) in the segmentation task, and the Duagman Rubber-Sheet Model was applied in the normalization. Then, a proposed CNN model is used to extract the features from the normalized irises. The proposed CNN contains four convolution layers, and each layer has been followed by a max-pooling layer, except the fourth that followed by a fully connected layer. Finally, the system used an SVM classifier to categorize the extracted CNN features.

Shanbagavalli et al. [31] proposed an approach for iris identification based on Emerging Mixed Convolutional and Adaptive Residual Network (EMiCoAReNet). The first phase in this approach is the data augmentation using different techniques such as rotation, cropping, flipping, and Color space transformations. The second phase is the iris feature extraction using a modified Gabor Filter. Finally, they used EMiCoAReNet to extract more features and used it for the classification task. The suggested approach achieves an accuracy rate of 95.2% on the CASIA-Iris-Interval dataset.

Gangwar and Joshi [32] proposed a Deep Convolutional Neural Network called DeepIrisNet. It composes eight convolutional layers followed by three fully connected layers. DeepIrisNet trained from scratch on some datasets, and it gives acceptable accuracy rates. The experiments in the paper [33] were based on five pre-trained deep CNN (VGG, AlexNet, ResNet, Google Inception, and DenseNet) to extract the features and use multi-class SVM for the classification. This approach was tested on two databases CASIA-Iris-Thousand and LG2200 dataset, by splitting the normalized images into training and testing datasets (70% for training and 30 % for testing).

Chakraborty et al. [34] suggested a texture-aware lightweight for deep CNN-based iris recognition. The proposed work is applied to the CASIA-Iris-thousand database and achieved a recognition rate of 94.7%, where this database contains 20000 images that have been split into training and test sets (80/20%). Moreover, an integrated framework using DL features was presented by Jayanthi et al. [12]. This framework was used for iris detection, segmentation, and recognition. The authors [12] used different pre-processing techniques such as Gamma correction, Median filtering and Bottom Hat filtering. For the iris localization, they used Hough Circle Transform. Finally, the authors used Mask R-CNN for iris segmentation and recognition.

Recently in 2022, Zambrano et al. [35] proposed a new iris recognition system based on a pre-trained CNN that extracts features from the iris images after applying many pre-processing stages. The proposed system used a pre-trained CNN that trained on the ImageNet dataset without fine-tuning that on the new iris datasets. In addition, based on a new ConvNet deep neural network, Jia et al. [36] proposed an iris recognition system. The system correlates the features extracted by many convolutional layers based on a multi-level interaction method. In addition, the system applied a mask network to exclude the noisy factor; this network has remarkably improved the system's performance.

Though the existing methods achieved an acceptable accuracy for iris recognition, many issues remain to be further addressed. We find that most systems apply many pre-processing steps to create a normalized iris image for use in the recognition process; these pre-processing steps affect the quality and computational efficiency of these systems. Furthermore, the high computational complexity in the feature extraction step, where several methods used deep CNN, contains tens to hundreds of millions of parameters. In addition, we find that some studies focused on iris recognition in large publicly available datasets, and others concentrated on small datasets. We also found some approaches evaluated on large and small datasets, but these approaches' performance decreased in one of these datasets. Also, some proposed systems evaluated on small datasets do not contain any main challenges that affect iris recognition. Other techniques have been evaluated on datasets containing a small number of classes.

B. *Motivations and contributions*

This work aims at proposing a robust and effective automatic iris recognition approach based on Deep Learning. Our approach makes the following contributions to overcome the limitations mentioned above:

- First, our proposed approach recognizes iris images after iris localization, without iris segmentation and normalization required by the iris recognition systems suggested in the literature [12], [32], [33]. That speeds up the iris recognition process and saves many computing resources.
- Second, we use a part of inception-v3 architecture pre-trained on ImageNet to extract features from the detected irises. We used the off-the-shelf inception-v3 features without fine-tuning them on the iris images datasets. The most significant benefit of these off-the-shelf features is saving training time and not needing a lot of data. Also, we reduced the model's complexity because we used just part of the inception-v3 architecture.
- Third, our proposed approach was validated using four benchmarks of different sizes, which contained different iris recognition challenges such as occlusions due to eyelash/ /glasses /eyelid, specular reflection, illumination variation, pupil dilation/constriction, and blur.

The main sections of this paper are organized as follows: We present a background on some popular Deep CNN models in section 2. The proposed approach is presented in section 3. Section 4 shows detailed experimental results with a comparison to the previous approaches. Finally, the paper concluded in Section 5.

2. Background

Deep Convolutional Neural Networks (CNN) achieved good performance in several fields, precisely in image classification and object detection. This section will review five popular models; we will first start with four models used in image classification (AlexNet, VGG16, ResNet50, and Inception-v3). Then, we will review the YOLO network used for object detection.

A. AlexNet

AlexNet is a Deep CNN proposed by Krizhevsky et al. [37] achieved high accuracy in the largescale ILSVRC challenge, where it outperformed other handcrafted methods. Eight layers were designed AlexNet: five convolutional layers, two of them not followed by max-pooling layers, and three fully-connected layers in the end. This paper used this deep CNN model to compare its accuracy rate with our proposed approach.

B. VGG 16

Simonyan end Zisserman [38] proposed a Deep CNN model called VGG16. This model achieved top-5 test accuracy of 92.7% on the ImageNet dataset. The VGG16 model used smaller filters (3×3) in the convolutional layer, reverse the AlexNet model that used (11×11 and 5×5) filters to improve performance. This Deep CNN model contains 13 convolutional layers, followed by ReLU, five max-polling layers, and three fully connected layers, followed by ReLU. The VGG16 model has been widely implemented due to its good generalization performance and simplicity. In this paper, we used VGG 16 model to compare its performance with our proposed approach.

C. ResNet50

He et al. [39] introduced the notion of residual connection to ameliorate the gradient flow in the network, where it establishes a shortcut path to bypass signal from block to the next block. The proposed ResNet-50 is a Deep model containing 48 convolutional layers, one 3x3 max-pooling layer, and a fully connected output layer; the number of parameters in ResNet50 is much smaller than VG16 and AlexNet. Also, we used this model in the experiments to show the efficiency of our proposed approach.

D. Inception-v3

The Inception-v3 model is proposed in [40]; Inception-v3 achieved high accuracy in object classification compared with Inception-v1 [41] and Inception-v2 [42] models, where it achieved an error of top 5 equal to 3.5 % on the ImageNet dataset. The inception-v3 model contains 46 layers, consisting of 11 Inception modules. Convolutional filter (1×1) is widely used in Inception-v3 to accelerate training speed, reduce the number of parameters, and reduce feature channels number. Briefly, in the object classification field, the state of the art is Inception-v3 [43].

E. YOLO

The YOLO (You Only Look Once) is an object detection network that achieved promising results in several tasks, such as face detection [44], medical face mask detection [45], iris detection [46]. Several models of YOLO have been proposed in the last years; the two most popular models are YOLOv4 and YOLOv4-tiny. YOLOv4 [47] is an object detection algorithm that achieved the best relation between speed and accuracy, where it has been optimized the network training, backbone, loss function, and activation function compared to YOLO-V3. To reduce the parameters, simplify the network structure, and improve real-time object detection, a light model called YOLOv4-tiny [48] was proposed based on YOLOv4. The YOLOv4-tiny model achieved extremely high speed compared with other YOLOv4 models.

3. Proposed Approach

The architecture of our proposed approach for iris recognition based on fine-tuned YOLOv4-tiny model and off-the-shelf inception-v3 features is shown in Figure 1.

We discuss the development of our proposed iris recognition approach in three parts: iris detection and cropping, features extraction, and classification.

A. The iris localization stage

In this stage, we localize and crop the iris region and input it into the CNN model. We used the iris region instead of the entire eye image to increase accuracy. To detect the iris region, we fine-tuned the YOLOv4-tiny model pre-trained on the MS COCO dataset, in which we annotated and used 400 iris images (70% Training, 20% Testing, and 10% Validation) selected from four different databases in this fine-tuning. The model was fine-tuned for 2000 epochs and has been able to achieve an iris detection accuracy rate reached to more than 98%. Figure 2 observed some examples of iris localization obtained based on the fine-tuned pre-trained YOLOv4-tiny. After the localization step, we cropped and resized all iris images to 299x299 and used it as an input in the CNN model to extract features, where the average size of the iris images after cropping is approximately 210x210 pixels.

B. The feature extraction stage

The inception-v3 achieved an accuracy rate of 94.4% in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), where it outperformed famous deep CNN models like AlexNet [37], VGG16 [38], and ResNet [39]. Recently, the inception-v3 [43] model was applied in several classification tasks and achieved high success [49], [50]. In this paper, we used the pre-trained Inception-v3 model to extract features, where we used a part of the off-the-shelf Inception-v3 model without any training. The Inception-v3 was pre-trained on the ImageNet database to classify 1 281 167 images into 1000 classes. The pre-trained Inception-v3 model needs an input image of size 299x299x3. It consists of a series of 11 inception modules. In our approach,

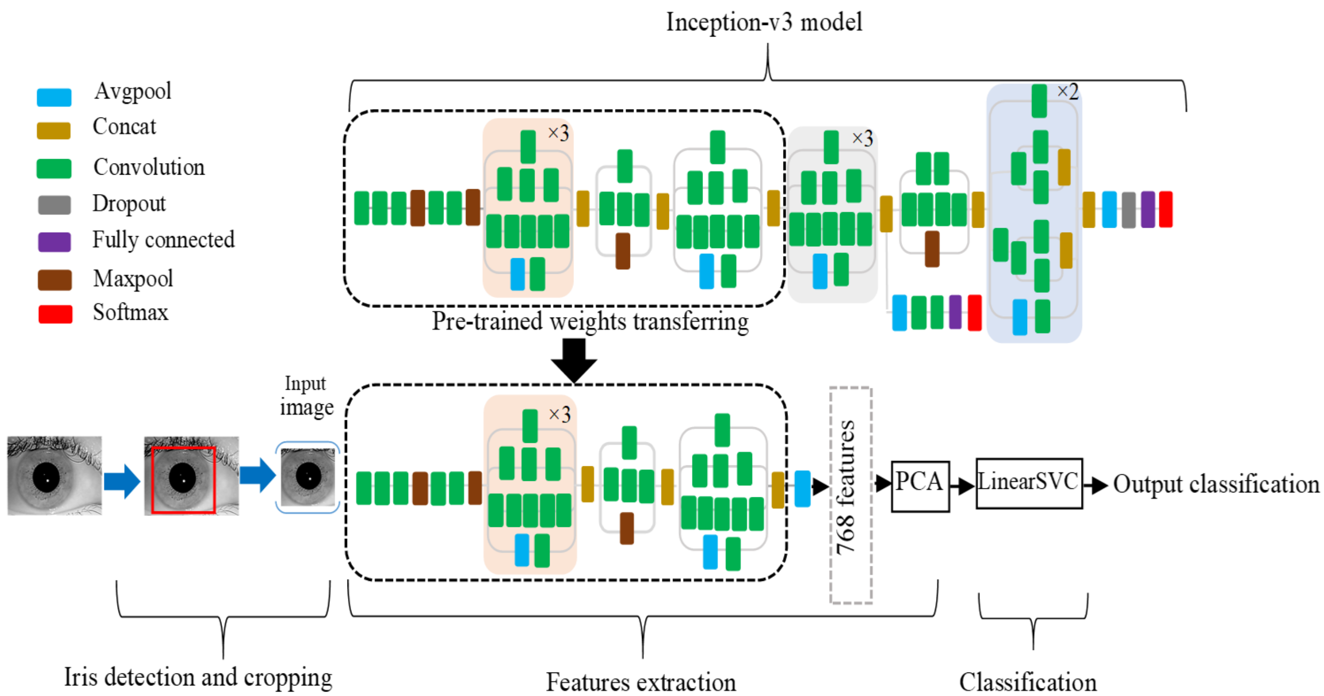


Figure 1. The architecture of our proposed approach.

we used only the first five inception modules to decrease the complexity of the proposed approach and increase its accuracy rate. We used five inception modules because we remarked that the accuracy rate dramatically degraded when we use less than five modules. Finally, and before the classification step, we applied Avgpool and PCA [51] to reduce the dimensionality.

C. Classification

Classification is the last step in the recognition process. It is used to assign a label to each test image.

Several types of classifiers were proposed and got excellent results in the literature, such as Support Vector Machine, Decision Trees, Random Forests, and Softmax Regression.The SVM classifier is a powerful tool for matching biometric features [18], [52], where it achieved a high accuracy rate in several iris recognition systems [18], [33], [21].

In our proposed approach, we used a fast and simple SVM algorithm called Linear Support Vector Classification (LinearSVC) [53].

LinearSVC is one of the most appropriate Machine Learning methods [54]. It is a type of SVM that adopts the term "one-vs-all," where LinearSVC uses a linear hyperplane between a class and the rest of the classes. The LinearSVC seeks to maximize the distances between a class and the other classes relying on the support vectors and the dimensional transformation.

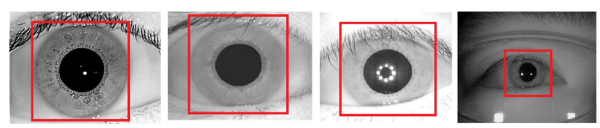


Figure 2. Samples of iris location obtained from four different databases.

4. Experiments

This work proposed an approach for iris recognition. The recognition accuracy rate of the proposed approach was evaluated on four public datasets (IITD, CASIA-Iris-V1, CASIA-Iris-Interval, CASIA-Iris-Thousand) collected under different conditions by applying five-fold Cross-Validation (5-fold CV), to involve all the parts of the databases for training and testing to obtain representative result (we utilized a class from scikit-learn called Stratified-KFold with enabling the shuffle attribute and random_state = 42). Also, we illustrate the performance of our approach by comparing their accuracy rate with some popular Deep Learning models and some state-of-the-art methods.

A. Data sets

1) IIT Delhi database

IIT Delhi [55] is an iris database that comprises 2240 iris images captured from 224 users from the students and staff at IIT Delhi (176 males and 48 females, their ages are about 14-55 years). IITD was collected using JPC1000, JIRIS, and digital CMOS cameras, under non-ideal conditions such as blur, specular reflections, eyelashes, and eyelids occlusion.

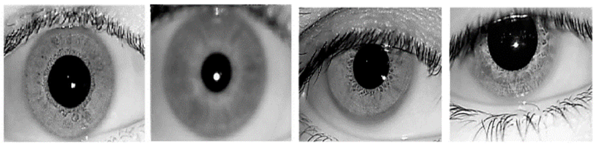


Figure 3. Samples from the IITD database.

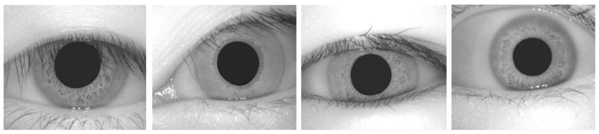


Figure 4. Iris images from the CASIA-Iris-V1 database.

The resolution of the IITD iris images is 320×240 pixels. Some samples from the IITD database are shown in Figure 3.

2) CASIA-Iris-V1 database

CASIA-Iris-V1 [56] was the first openly accessible irises database, collected by the National Laboratory of Pattern Recognition, Institute of Automation, CASIA. This database contains 756 iris images from 108 different eyes. For each eye, seven images were captured in two sessions (3 samples in the first session and 4 in the second session).

CASIA-Iris-V1 was collected using a custom NIR camera. The pupil of iris images was edited with a circular region of a constant intensity value to mask out the specular reflections. The resolution of the CASIA-Iris-V1 images is 384×256 pixels. Figure 4. shows some images from the CASIA-Iris-V1 database containing occlusions due to eyelashes/ eyelids.

3) CASIA-Iris-Interval database

CASIA-Iris-Interval [57] is an iris image dataset comprises 2,655 images from 395 eyes of 249 individuals was collected using the same sensor as CASIA-Iris-V1, using a strong illumination to obtain a very rich iris texture. The CASIA-Iris-Interval introduced some challenges such as occlusions due to eyelashes/ eyelids, specular reflection, and pupil dilation/constriction. The number of simples was not fixed for each class (eye). CASIA-Iris-Interval contains 153 classes with an image number of seven; these classes are selected to be used in this study. The resolution of the CASIA-Iris-Interval images is 320×280 pixels.Some iris images from this database are shown in Figure 5.

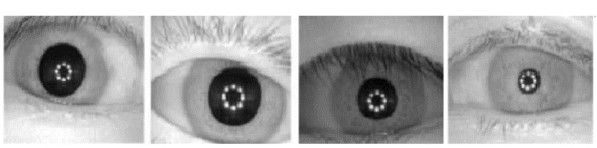


Figure 5. CASIA-Iris-Interval database.

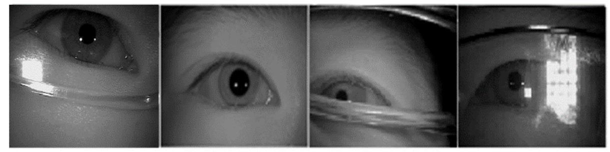


Figure 6. Samples from the CASIA-Iris-Thousand database.

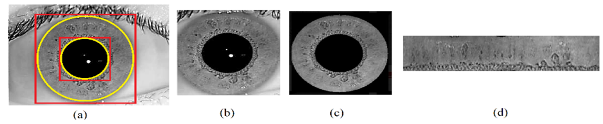


Figure 7. The result of cropped, segmented, and normalized iris images. (a) detected iris and pupil boundary, (b) cropped iris region, (c) segmented iris, (d) normalized iris.

4) CASIA-Iris-Thousand database

CASIA-Iris-Thousand [58] is an iris image dataset that contains 20,000 images from 2000 eyes of 1000 persons; there are ten right and ten left eyes images for each person. It was collected using the IKEMB-100 camera manufactured by IrisKing.The resolution of the CASIA-Iris-Thousand images is 640×480 pixels.

This database was the first openly accessible irises database containing one thousand different people. It is highly useful to evaluate new recognition models with this dataset, where iris recognition is a more challenging task because some images contain eye-glasses, pupil dilation/constriction and strong specular reflections, which expand the intra-class variation. We can see some samples from the database in Figure 6.

A summary of iris databases used in our experiments is presented in Table I.

B. *Experimental result*

We have accomplished several experiments to prove the proposed approach's robustness, where we divided this section into three sub-sections. We used the iris region images in the first sub-section (main experiments). In addition, we used segmented and normalized iris images in the second sub-section (additional experiments). Figure 7. shows three types of iris images used in our experiment (b, c, d). In the third sub-section, we compared our results to state-of-the-art methods.

1) Main experiments

We evaluated our approach on four public datasets collected under different conditions, where we used iris region images localized based on the YOLOv4-tiny model.

In this section, we accomplished four experiments on each database. In the first experiment, we computed the accuracy rate of our proposed approach.

In the second, we trained some popular deep CNN models from scratch to compare their performance with

TABLE I. Overview of iris databases used in our experiments, Where ”/” signifier the no existence of challenge, ”+” signifies the existence of the challenge and ”++” signifies that the challenge degree’ is high.

Dataset	Occlusions	Reflecions	Illumination	Blur	Resolution	Classes×simples
IITD	+	+	/	+	320×240	224×10
CASIA- Iris-V1	+	/	/	/	384×256	108×7
CASIA-Iris-Interval	+	++	+	/	320×280	153×7
CASIA-Iris-Thousand	++	+	++	/	640×480	2000×10

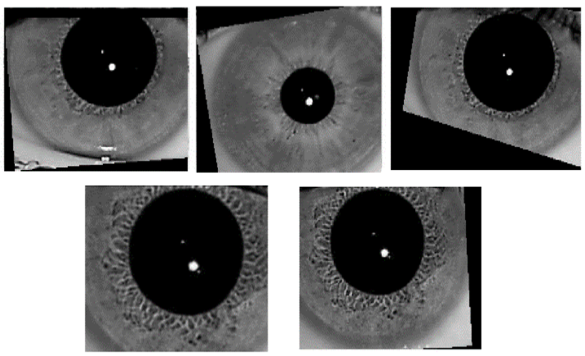


Figure 8. Samples from the IITD database after applying the Data Augmentation technique.

the performance of our approach. We used the deep CNN models without any modification only in the output layer, where we changed the number of neurons to equal the number of classes in the dataset.

In the third experiment, to improve the accuracy rate of the deep CNN models, we augmented the training set using data augmentation techniques. We used different geometric transformations in constant fill mode: height and width shifting in ranges 0.2, rotation in the range of 15 degrees, and zooming in the range of 0.15. Figure 8 illustrates some iris images generated by data augmentation from the IITD database.

In the fourth, we used the ImageNet pre-trained models to achieve more performance, where we trained only the classification layers. Before we started, we presented a summary of the architectures used in our experiments. (see Table II)

a) Experiment on ITTD database

The IITD database is selected to test and evaluate our proposed approach because their iris images it captured under different conditions such as reflections, occlusions, and blur. Our approach obtained a high accuracy rate on the IITD database (99.91%). (See Figure 9), where it failed to recognize only two iris images among 2240 testing images. The two images were captured under very bad conditions: blur and eyelashes occlusion, Figure 10. shows these images.

- *Comparison of the performance of our approach with some popular deep CNN models trained from scratch:*

We trained the models from scratch on the IITD database, where the Inception-v3, AlexNet, and ResNet50 achieve an acceptable accuracy rate compared to VGG16, in which Inception-v3 achieved 97.25%, AlexNet and ResNet50 achieved 97.68% and 97.48%, respectively. Still, our proposed approach accuracy rate is better than their accuracy, where our approach achieved 99.91%. For more details, see Figure 9. The models trained from scratch failed to achieve a high accuracy because the database used for training is small, but the deep CNN models require a large amount of data.

- *Comparison of the performance of our approach with some popular deep CNN models trained from scratch using Data Augmentation:*

We trained the models on the IITD database with data augmentation; the performance of Inception-v3 with data augmentation is improved compared with the accuracy rate obtained without data augmentation, where it achieved 98.93%. Still, the accuracy rates of these models are worse than the accuracy achieved by our proposed approach (see Figure 9). The data augmentation technique failed to achieve an accuracy rate more than that been achieved by our approach. In the next experiment, we will use the Transfer Learning technique to achieve more accurate rates.

- *Comparison of the performance of our approach with some popular pre-trained deep CNN models:*

The performance of the ImageNet pre-trained AlexNet, VGG16, and inception-v3 models is higher than that obtained by the models trained from scratch with data augmentation. Despite of that, the performance of our approach is the best. (see Figure 9)

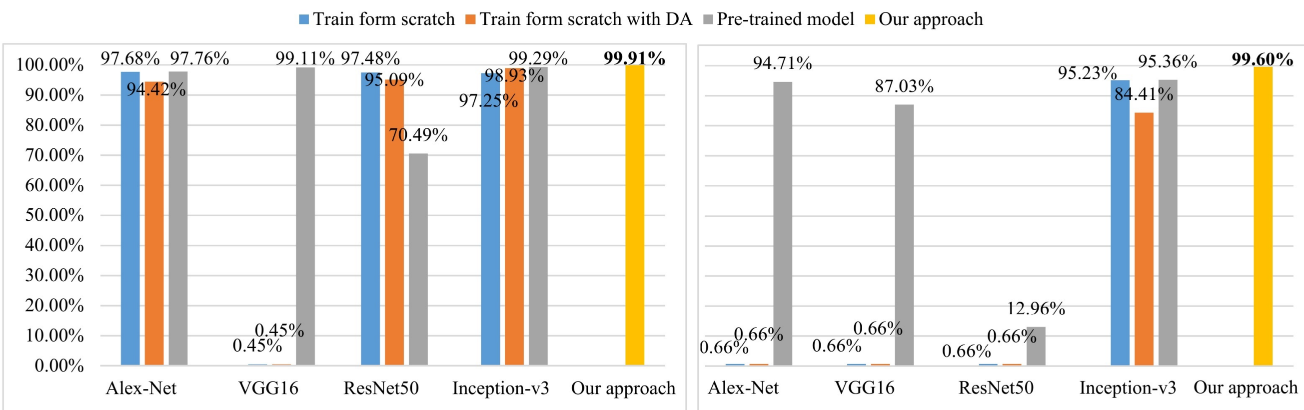
To summarise, on the IITD database, the inception-v3 achieved high results compared to the other famous models (AlexNet, VGG16, ResNet50), in which the pre-trained inception-v3 model surpassed all the models in all the scenarios. However, our proposed approach outperformed the pre-trained inception-v3.

b) Experiment on CASIA-Iris-V1 database

The CASA-Iris-V1 is the first openly accessible irises

TABLE II. Overview of the architectures used in our experiments.

Architecture	Inputs size Parameters	The final output	feature map size
AlexNet	224*224	60.97 M	6 x 6 x 256
ResNet 50	224*224	25.56 M	2048
VGG 16	224*224	138.36 M	7 x 7 x 512
Inception-v3	299*299	23.85 M	2048
The architecture used in our approach	299*299	3.45 M	768



(a) (b)

Figure 9. The recognition accuracy of different models compared with our approach accuracy rate on : (a) the IITD dataset, (b) the CASIA-Iris-V1 dataset

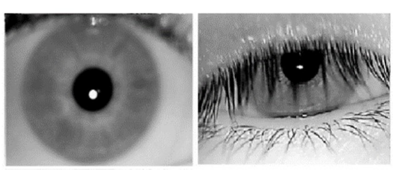


Figure 10. The two iris images from the IITD database failed to recognize by our approach.

database, where it contains some occluded iris images. Our approach achieved high performance on the CASIA-Iris- V1 database, where it achieved a 99.60 % recognition accuracy. Figure 9 shows that.

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch:*

We trained the models AlexNet, VGG16, ResNet50, and Inception-v3 from scratch on the CASIA-Iris-V1 database. Compared with the other models, only the Inception-v3 model achieved an acceptable accuracy, with 95.23% recognition accuracy (see Figure 9). But this accuracy is very low compared to the accuracy rate achieved by our approach accuracy.

In the next experiment, we will use the Data Augmentation technique to improve the accuracy rates of the CNN models.

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch using Data Augmentation:*

The data augmentation technique failed to improve the accuracy rate of the four models. Figure 9 illustrates that.

• *Comparison of the performance of our approach with some popular pre-trained deep CNN models:*

The ImageNet pre-trained models achieved higher recognition accuracy than those trained from scratch with and without data augmentation, where they achieved 94.71%, 87.03%, and 95.36%, for AlexNet, VGG16 and Inception-v3, respectively. Despite that, these accuracy rates are very low compared with our approach performance, which achieved excellent results. (See Figure 9)

To summarise, on the Casia-v1 database, the Inception-v3 surpassed the AlexNet, VGG16, and ResNet50 models, where the pre-trained Inception-v3 had an accuracy rate of 95.36. However, this accuracy is lower than our proposed approach's accuracy rate.

c) Experiment on CASIA-Iris-Interval Database

We chose the CASIA-Iris-Interval Database to evaluate

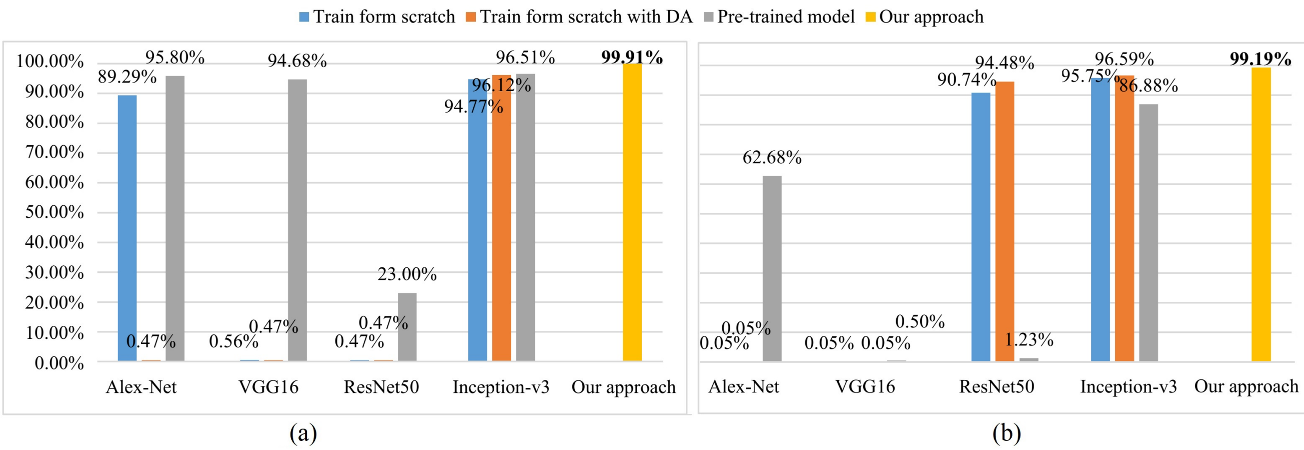


Figure 11. The recognition accuracy of different models compared with our approach accuracy rate on : (a) the CASIA-Iris-Interval dataset, (b) the CASIA-Iris-Thousand dataset

the performance of our proposed approach because their iris images are collected under different conditions strong reflections, occlusions, and uncontrolled illumination. Our approach achieved an extremely high accuracy rate (99.91%) on this dataset (see Figure 11)

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch:*

We compared our accuracy rate with some Deep CNN models: AlexNet, VGG16, ResNet50, And Inception-v3; these models were trained from scratch on the CASIA-Iris-Interval without Data Augmentation. The best accuracy rates were achieved by AlexNet and Inception-v3 (89.29%, and 94.77%, respectively). Our approach achieved a very high accuracy rate compared with these accuracies. Figure 11 illustrates that.

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch using Data Augmentation:*

In this experiment, we used Data augmentation to improve the accuracy rates of the Deep CNN models. With the data augmentation technique, the accuracy rate of the Inception-v3 improved by 1.35%, but the improved accuracy rate (96.12%) is lower than the accuracy rate achieved by our proposed approach. (see Figure 11).

• *Comparison of the performance of our approach with some popular pre-trained deep CNN models:*

In this experiment, we used the Deep CNN models pre-trained on ImageNet to improve the accuracy rate of the different models on the Casia-Iris-Interval database. AlexNet and VGG16 models achieved a high accuracy rate compared with the accuracy achieved by the training from scratch. Still, these new accuracies are significantly lower compared to the accuracy rate obtained by our approach. (See Figure 11)

To summarise, on the Casia-Iris-Interval database, the pre-trained AlexNet, VGG16, and Inception-v3 models achieved high accuracies compared with other scenarios. However, our accuracy rate outperformed these accuracies.

d) Experiment on CASIA-Iris-Thousand Database

CASIA-Iris-Thousand database is mainly used to evaluate models proposed for iris recognition because it contains significant challenges that reduce the accuracy recognition. CASIA-Iris-Thousand iris images are captured under uncontrolled conditions: reflections, heavy occlusion, and illumination variation. Also, there is another challenge; CASIA-Iris-Thousand contains 2000 classes with only ten simples for each class. Despite these challenges, our approach achieved an average accuracy of 99.19% on this database. (see Figure 11)

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch:*

We trained four models from scratch on the CASIA-Iris-Thousand database, where the ResNet50 and Inception-v3 achieved an acceptable accuracy rate compared to AlexNet and VGG16, in which ResNet50 achieved 90.74%, and Inception-v3 achieved 95.75%. The accuracy rates achieved in this experiment are lower than our proposed approach accuracy. (see Figure 11).

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch using Data Augmentation:*

To improve the accuracy rate of the Deep CNN models, we augmented the training set by using different geometric transformations. The data augmentation improved the accuracy rate of the Inception-v3 model to 96,59%. Despite that, the accuracy rate of our approach is the highest. Figure 11 illustrates that.

• *Comparison of the performance of our approach with some popular pre-trained deep CNN models:*

In this experiment, we used the Deep CNN models pre-trained on ImageNet to compare the accuracy rate of the different models on the CASIA-Iris-Thousand database with the accuracy rate of our approach. The Inception-v3 model has achieved the best accuracy rate in this experiment with 86.88%, but this accuracy rate is significantly lower than the accuracy achieved by the training from scratch. Figure 11 shows that.

To summarise, on the Casia-Iris-Thousand database, the models ResNet50 and Inceptions-v3 that train from scratch with DA achieved high accuracies compared with other scenarios. However, these accuracies are lower than our proposed approach's accuracy rate.

2) Additional experiments

In this section, we conduct additional experiments to evaluate the effectiveness of the proposed approach. In this experiment, we used segmented iris images and normalized iris images, where we compared their accuracy rates to our approach that used iris region images.

We compared the accuracy rates of the different types of iris images (iris region images, segmented iris images, and normalized iris images) to prove the correctness of our choice for the type of iris image we used in our approach.

This section is divided into two subsections; in the first subsection, we conduct experiments based on segmented iris images, but our experiments are based on normalized images in the second subsection.

a) Iris recognition using segmented iris images

We used YOLOv4-tiny to detect iris and pupil, and then we determined the boundary of iris and pupil using circles. Finally, we replaced the regions outside iris boundaries with constant intensity to mask the challenges of eyelashes and specular reflections. Figure 12 illustrates the process of iris segmentation.

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch using segmented iris images:*

We trained the models from scratch on four databases using segmented iris images. The Inception-v3 achieved an acceptable accuracy rate on all databases, where it achieved 92.73%, 96.65%, 96.25%, and 94.48% on the CASIA-Iris-V1, IITD, Casia-Iris-Interval, and CASIA-Iris-Thousand databases, respectively. On the IITD database, the AlexNet and the ResNet50 models achieved 94.05% and 98,51%, respectively. On the CASIA-Iris-Thousand, the Resnet50 model achieved 85.85%.(See Table III)

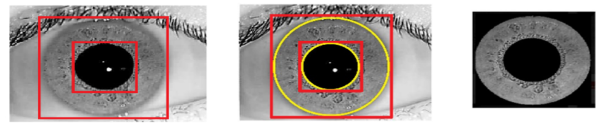


Figure 12. Process of iris segmentation..

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch with data augmentation using segmented iris images:*

We used the data augmentation technique to improve the accuracy rate of the Deep CNN models. Still, the accuracy rate of the different models is lower than our proposed approach on the four databases.

The accuracy rate of the Inception-v3 improved to 93.78%, 97.50%, 96.32%, and 95.01% on the CASIA-Iris-V1, IITD, CASIA-Iris-Interval, and CASIA-Iris-Thousand databases, respectively. But these results are significantly lower compared with our approach accuracy rates. (see Table III)

• *Comparison of the performance of our approach with some popular pre-trained deep CNN models using segmented iris images:*

In this experiment, we used the Deep CNN models on ImageNet to improve the accuracy rate of the different models. The AlexNet models achieved a higher accuracy rate in this experiment than the training for scratch, where it achieved 95,22%, 84.53%, and 85.34% on the IITD, CASIA-Iris-V1, and CASIA-Iris-Interval databases, respectively. Also pre-trained VGG16 model achieved accuracy rates better than the VGG16 trained from scratch. Despite of that, the results achieved by the pre-trained models are significantly lower than our proposed approach. (see Table III)

In addition, we compared the results achieved by our proposed feature extraction model followed by LinearSVC with our approach, where our feature extraction model extracted features from the segmented iris images and used LinearSVC in the classification task. The proposed feature extraction model achieved an excellent accuracy rate compared with other models. Still, its accuracy rate is lower than our approach that extracts features from iris region images, in which our feature extraction model achieved 98,54%, 99.33%, 99.35%, and 97.50% on the CASIA-Iris-V1, IITD, CASIA-IrisInterval, and CASIA-Iris-Thousand databases, respectively. Table III illustrates that.

To summarise, on the four iris databases, the Inception-v3 model achieved high results when it extracted features from the segmented iris images. However, our feature extraction model with LinearSVC outperformed these results. In addition, our proposed approach that used iris region images outperformed all models that used segmented iris

TABLE III. The recognition accuracy of different models that used segmented iris images compared with our approach accuracy rates on the four databases.

Datasets	Type of Training	AlexNet	VGG16	ResNet50	Inception-v3	Our proposed feature extraction model + LinearSVC	Our approach
IITD	From scratch	94.05%	0.45%	98.51%	96.65%	99.33%	**99.91%**
	Scratch with DA	93.80%	0.45%	96.70%	97.50%		
	Pre-trained	95.22%	81.03%	66.61%	97.10%		
CASIA-V1	From scratch	31.15%	0.92%	0.66%	92.73%	98.54%	**99.60%**
	Scratch with DA	0.66%	0.66%	0.79%	93.78%		
	Pre-trained	84.53%	92.86%	40.29%	92.36%		
CASIA-Iris-Interval	From scratch	29.25%	0.56%	0.47%	96.25%	99.35%	**99.91%**
	Scratch with DA	0,56%	0.47%	0.47%	96.32%		
	Pre-trained	85.34%	64.90%	45.53%	89.78%		
CASIA-Iris-Thousand	From scratch	0.05%	0.05%	85.85%	94.48%	97.50%	**99.19%**
	Scratch with DA	0.05%	0.05%	93.32%	95.01%		
	Pre-trained	0.46%	0.30%	3.73%	74.02%		

images.

b) Iris recognition using normalized iris images

We used YOLOv4-tiny to detect iris and pupil, and then we determined the boundary of iris and pupil using circles. Finally, we used Daugman's rubber sheet model [3], [59] to create a normalized iris image. In this experiment, we used normalized images with a fixed size of 80x512. This size is recommended in the works of literature [60]. Figure 13 illustrates the process of iris normalization.

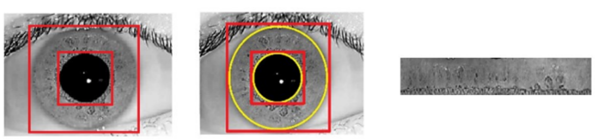


Figure 13. Process of iris normalization.

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch using normalized iris images:*

This experiment trained the deep CNN models from scratch on four databases using normalized iris images. The AlexNet achieved accuracy rates of 95.09%, 81.08%, 85.81% on the IITD, CASIA-Iris-V1, CASIA-Iris-Interval databases, respectively. The Inception-v3 trained from scratch achieved an acceptable accuracy rate on the four databases: 90.56%, 97.63%, 90.73%, and 91.14% on the CASIA-Iris-V1, IITD, CASIA-Iris-Interval, and CASIA-Iris-Thousand databases, respectively. Also, on the IITD and the CASIA-Iris-Thousand databases, the Resnet50 model achieved 97.99% and 88,48%, respectively. (See Table IV)

• *Comparison of the performance of our approach with some popular deep CNN models trained from scratch with data augmentation using normalized iris images:*

Data augmentation technique improved the accuracy rate of the Inception-v3 model, where it achieved 98.08%, 92.40%, and 93.40% on the IITD, CASIA-Iris-Interval, and CASIA-Iris-Thousand databases, respectively. But these accuracies are significantly lower compared with the performance of our approach. (see Table IV)

• *Comparison of the performance of our approach with some popular pre-trained deep CNN models using normalized iris images:*

In this experiment, we used the Deep CNN models pre-trained on ImageNet to classify normalized iris images. These models achieved bad results, where their accuracy rates did not exceed 86,85%, 95,22%, 85,70%, and 71,77% on the CASIA-Iris-V1, IITD, CASIA-Iris-Interval, and CASIA-Iris-Thousand databases, respectively. (See Table IV)

In addition, in this experiment, we compared the results achieved by our proposed feature extraction model followed by LinearSVC with our approach, where we entered the normalized iris image in our proposed feature extraction model and used LinearSVC in the classification stage. Using normalized iris images with our feature extraction model, we achieved good accuracy rates compared with other models . Still, these results are lower than the accuracy rates of our proposed approach, where our feature extraction model achieved 98.41%, 99.38%, 99.16%, and 97.07% on the CASIA-Iris-V1, IITD, CASIA-Iris-Interval, and CASIA-Iris-Thousand databases, respectively. (See Table IV)

To summarise, on the four iris databases, the Inception-v3 model achieved acceptable accuracies when it used the normalized iris images. However, our feature extraction

TABLE IV. The recognition accuracy of different models that used normalized iris images compared with our approach accuracy rates on the four databases.

Datasets	Type of Training	AlexNet	VGG16	ResNet50	Inception-v3	Our proposed feature extraction model + LinearSVC	Our approach
IITD	From scratch	95.09%	0.45%	97.99%	97.63%	99.38%	**99.91%**
	Scratch with DA	57.05%	0.45%	92.95%	98.08%		
	Pre-trained	89.24%	35.31%	23.13%	95.22%		
CASIA-V1	From scratch	81.08%	0.66%	0.66%	90.56%	98.41%	**99.60%**
	Scratch with DA	16.85%	0.66%	0.79%	85.47%		
	Pre-trained	84.92%	83.73%	4.75%	86.85%		
CASIA-Iris-Interval	From scratch	85.81%	0.47%	0.47%	90.73%	99.16%	**99.91%**
	Scratch with DA	0.47%	0.47%	0.47%	92.40%		
	Pre-trained	78.34%	62.00%	1.70%	85.70%		
CASIA-Iris-Thousand	From scratch	0.05%	0.05%	88.48%	91.14%	97.07%	**99.19%**
	Scratch with DA	0.05%	0.05%	90.90%	93.40%		
	Pre-trained	34.22%	0.19%	1.29%	71.77%		

model with LinearSVC surpassed these accuracies. In addition, our proposed approach that used iris region images surpassed all models that used normalized iris images.

3) Comparison to State-of-the-art methods

In this part, we compared our proposed approach with current state-of-the-art methods used in the iris recognition field.

To the best of our knowledge, our proposed approach outperforms the state-of-the-art methods evaluated on the IITD database, except the methods proposed in [24] and [25] that evaluated with a subset containing only 60 classes. For this, they obtained good results. But, in our experiments, we used 224 classes.

We applied five-fold cross-validation to test the proposed approach on all iris images on the IITD database; despite that, we surpassed the methods tested on only a subset of the IITD database. Where the proposed approach achieved an accuracy rate of 99.91%. In addition, our approach achieved 99.73% by randomly splitting the dataset (50% for training, and 50% for testing). Table V illustrates that.

On the CASIA-Iris-V1, the accuracy rate of our approach surpassed the state-of-the-art techniques, where Kranthi Kumar et al. [29] achieved an accuracy rate of 98% and Alaslni et al. [25] achieved 98.3% despite the second method being evaluated on only 60 classes. On the other hand, the proposed approach achieved an average accuracy rate, up to 99.60%. (See Table V).

On the CASIA-Iris-Interval, our method outperforms the state-of-the-art methods. Despite using 153 classes to evaluate our approach, we surpassed some recent methods evaluated with 60 or 100 classes. Our proposed approach achieved an accuracy rate of 100% on the CASIA-Iris-Interval by choosing randomly six iris images for training and one image for testing, 100% in the case of five images for training and two for testing and 99.91% if it used five-fold cross-validation protocol.

On CASIA-Iris-Thousand, the proposed approach achieved an average accuracy rate of 99.19% using five-fold cross-validation and 99.05% if we randomly split the data into 30% for testing and 70% for training. To the best of our knowledge, 99.19% is the best accuracy rate achieved on the CASIA-Iris-Thousand.

The method proposed by Nguyen et al. [33], the T–Center method [11], and Jayanthi et al.[12] achieved good results on the CASIA-Iris-Thousand. But, the main problem of Nguyen et al. [33] and the T–Center [11] methods is the pre-processing step's complexity because both methods are based on extracting features from normalized iris images. Also, the T–Center [11] method could not achieve good results in the small database compared with our approach, where the proposed approach outperformed this method on the IITD database (see Table V). But, the method in [33] is not evaluated on small databases. On the other hand, the framework in [12] used Mask R-CNN that contain tens of millions of parameters. Moreover, the main challenge in the Mask R-CNN is the large number of hyper-parameters that need to be tuned. Still, the authors did not present any technique to perform hyper-parameter tuning for the proposed DL model.

Overall, the accuracy rates on the four iris image databases show the proposed approach's robustness and effectiveness against illumination variation, occlusion, reflections, and blur.

TABLE V. The accuracy rates of state-of-the-art iris recognition methods are compared with our proposed approach, where "Yes" or "No" means that the method uses the iris normalization or not

Datasets	Method	Recognition Accuracy	Number of classes	Normal-ization	Evaluation protocol
IITD Iris	Winston and Hemanth [16]	98.4%	/	Yes	Train: 60%, Test: 40%
	Minaee et al. [23]	99.4%	224	No	Train: 50%, Test: 50%
	Alaslani [24]	100%	60	No	Train: 80%, Test: 20%
	Alaslni et al [25]	100%	60	No	Train: 80%, Test: 20%
	Arora and Bhatia [26]	98%	224	Yes	Train: 60%, Test: 20%, Val : 20%
	Yifeng Chen et al. [11]	99.30%	224	Yes	Train: 80%, Test: 10%, Val : 20%
	Sujana and Reddy [27]	98.05%	224	Yes	Train: 80%, Test: 20%
	Shanto et al. [28]	98%	25	No	Train: 60%, Test: 20%, Val : 20%
	Our Approach	**99.73%**	224	No	Train: 50%, Test: 50%
		99.91% ±0.20%	224	No	5-fold CV
CASIA Iris-V1	Dua et al. [17]	97%	108	Yes	/
	Abdo el al. [18]	98.15%	100	Yes	Train: 4/7, Test: 3/7
	Alaslani [24]	98%	60	No	Train: 80%, Test: 20%
	Alaslni et al [25]	98.3%	60	No	Train: 80%, Test: 20%
	Sujana and Reddy [27]	95.4%	108	Yes	Train: 80%, Test: 20%
	Kranthi Kumar et al [29]	98%	108	Yes	Train: 80%, Test: 20%
	Hassan et al. [30]	99.07%	108	Yes	Train: 70%, Test: 15%, val: 15%
	Our Approach	**99.60% ±0.36%**	108	No	5-fold CV
CASIA-Iris Interval	Abdo et al. [18]	99%	100	Yes	Train: 4/7, Test: 3/7
	Khotimah and Juniati [20]	92.63%	10	Yes	5-fold CV
	Abdo et al. [21]	100 %	100	Yes	Train: 6/7, Test: 1/7
		98.50%	100	Yes	Train: 5/7, Test: 2/7
		96.67%	100	Yes	Train: 4/7, Test: 3/7
	Abdalla et al. [22]	100%	100	Yes	Train: 6/7, Test: 1/7
		99%	100	Yes	Train: 5/7, Test: 2/7
		97%	100	Yes	Train: 4/7, Test: 3/7
	Alaslani [24]	89%	60	No	Train: 80%, Test: 20%
	Alaslni et al. [25]	91.6%	60	No	Train: 80%, Test: 20%
	Shanbagavalli et al [31]	95.2%	/	No	Train:4-9 samples, Test : 1 samples
	Our Approach	**100%**	153	No	Train: 6/7, Test: 1/7
		100%	153	No	Train: 4/7, Test: 3/7
		99.91% ±0.21%	153	No	5-fold CV
CASIA-Iris Thousand	Minaee et al.[23]	90%	2000	No	Train: 50%, Test: 50%
	Alaslani [24]	98%	60	No	Train: 80%, Test: 20%
	Alaslni et al. [25]	95%	60	No	Train: 80%, Test: 20%
	Gangwar and Joshi [32]	93.4%	2000	Yes	Train: 80%, Test: 20%
	Nguyen et al. [33]	98.80%	2000	Yes	Train: 70%, Test: 30%
	Chakraborty et al. [34]	94.7%	2000	No	Train: 80%, Test: 20%
	Jayanthi et al. [12]	98.75%	2000	Yes	Train: 80%, Test: 10%, Val :10%
	Yifeng Chen et al. [11]	99,14%	2000	No	Train: 75%, Test: 25%
	Our Approach	**99.05%**	2000	No	Train: 70%, Test: 30%
		99.19% ±0.14%	2000	No	5-fold CV

5. Conclusions and future work

This paper proposes a robust approach for iris recognition; we used ImageNet pre-trained Inception-v3 model for extracting features and LinearSVC for the classification. Our approach used fine-tuned YOLOv4-tiny to detect the iris region, and then we cropped the iris region image before starting the process of features extraction. The proposed approach is characterized by using the iris region image without any pre-processing, such as segmentation and normalization; also, it used only five inception modules of the pre-trained inception-v3 model without any fine-tuning. All this enables us to save computational time and resources.

Our approach strongly resists to the different iris recognition challenges, such as occlusions due to eyelash/ /glasses /eyelid, specular reflection, illumination variation, pupil dilation/constriction, and blur.

The proposed approach outperforms state-of-the-art methods proposed for iris recognition. It achieved a high accuracy rate up to 99.60%, 99.91%, 99.91%, and 99.19% on the CASIA-Iris-V1, IITD, CASIA-Iris-Interval, and CASIA-Iris-Thousand databases, respectively.

In future work, we intend to adapt our approach for face recognition. Then we plan to extend the proposed approach by proposing a multimodal approach based on the face and both irises for biometrics recognition.

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