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A Multi-Type Convolutional Neural Networks for Improved Iris Classification

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ABSTRACT: Iris recognition is a biometric technology widely used in applications including border control, voter registration, and mobile authentication. However, variations in light, reflection, and noise in the image cause issues with accurate recognition. This paper presents a two-stage iris recognition system. The first stage segmentations and detection of the iris is performed using the HoughCircles algorithm, as well as inpainting the image to enhance image quality and remove any shading or artifacts. The second stage uses novel multi-type neural convolutional network that combines standard, spatial, and depthwise convolutions as part of its feature extraction and classification. The proposed model is evaluated on the MULBv1 dataset to obtain 98.21% classification accuracy and a 98.16% F1-score. The results demonstrate the model's efficacy for use in real-world iris identification systems.

Keywords: Iris, Segmentation, Classification, CNN, Biometric, Spatial Convolution, Depthwise Convolution.

1. INTRODUCTION

Over the past few years, however, security and privacy preserving technologies have made strides especially within the authentication systems category. The systems have come to play a significant role in numerous online and offline real-world applications. Generally, authentication can be either password-based or biometric based. These groups each have their own concept of use case, advantage, and limitation [1]. Iris-based recognitions systems are among the biometric solutions and use of these systems has drawn considerable research attention because of their high accuracy and security. It is widely used in several areas like unlocking smartphones, border and immigration verification, financial transfers, and security checks at airports etc [2,3]. The anatomical data based on the important locations of iris landmarks are also useful in other applications such as human-computer interaction, identification of an individual and even in superior security systems [4]. As more secure methods of biometric authentication have become desirable to ensure privacy yet reproduce a high level of reliability, iris recognition has been providing increasing benefits as a point of safety because of its unique protocol of acquisition of information and reliability. However, the accuracy that the systems of iris recognition operate is quite dependent on the nature of the photographs of the iris captured and it is also of vital importance to the optimization of the performance [5]. Iris recognition is one of the best and most efficient systems of biometric technologies among the range of some others [6,7]. Information theory concepts point to the striking high values of entropy and extreme longevity of the texture of the iris throughout an individual's life [8-10]. The iris experiences minor changes throughout early childhood but after adulthood, the structure does not vary significantly and therefore this makes the iris useful in long-term identification operations [11]. The human iris is a complex and unique structure, anatomically, consisting of pupillary zone, which is the area surrounding the pupil, the ciliary zone, comprising peripheral area and the collarette, acting as a barrier between the two regions. The fine textures and complicated designs of the iris are developed prenatally and have little or no genetic control. Consequently, the patterns of iris do not match even among identical twins and they do not match the left and right iris of the same person [12-14]).

Iris recognition systems have been mostly based on the use of the near infrared NIR and dedicated sensor technology to derive high quality iris images [15]. Nevertheless, the images acquired are commonly contaminated by a range of noise factors including specular reflections, motion and occlusions by eyelashes which are all major challenges to the process

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of iris recognition [16]. There is a standard iris recognition method that is generally composed of four stages: Capture Image, extract iris region, normalize iris region and extract features and match. Even though NIR imaging is widely used in practice because it helps to minimize visual noise, the recent interest in building an iris recognition system under visible light conditions has been observed, particularly in the context of low-end consumer applications smartphones, and embedded cameras [17]. In typical iris normalization, by a polar coordinate transformation, the annular portion of iris is mapped to rectangular form via the system. This representation of a matrix in a rectangular format helps to code the discriminative features to be compared and classified [18,19]. Traditionally, iris recognition techniques have been reliant upon handcrafted features, features that are designed using domain knowledge through means that are handcrafted. Those features are calculated following the segmentation of the iris and are to be used to carry information about the texture/edge/frequency. Nevertheless, there are a number of limitations that are associated with such traditional practices. They also frequently need considerable preprocessing and parameter tuning and modification to work averagely on a dataset. In addition, this use of human-designed features limits the capacity of the model to learn high level abstract representations and consequently the capability of the model to generalize and make accurate recognition [20].

The invention of the methods of deep learning, namely Convolutional Neural Networks CNNs has greatly promoted the area of biometric recognition, i.e., iris-based biometric identification systems. Such models have proven to have excellent performance in handling problems like occlusions, volatility of environmental conditions and cross-modality recognition, which are part and parcel of the inherited hassles [21,22]. The limitations imposed by the traditional mechanisms of iris recognition, e.g., the use of handcrafted features, the noise sensitivity, have prompted the move toward the adoption of a CNN-based architecture in order to perform the feature extraction in a robust and automated manner. Earlier studies in this field have discussed the application of established CNN models such as: AlexNet, GoogLeNet, ResNet50, and in many cases employed transfer learning to use pre-trained architectures in the context of iris recognition [23]. Even with the life-altering effects of deep learning on the use of computer vision, the existing methods still have a number of issues. Most conspicuously, the performance of CNNs can be highly reliance on the access of large and high-quality and mostly non-verbal datasets which are expensive and take time to retrieve, annotate, and process [24]. Such constraints act as constant challenges to the extensive implementation of deep learning models in practical systems of iris recognition.

To address the problems mentioned above, the present research proposes a HoughCircles algorithm-based process for iris image segmentation, followed by contrast enhancement and grayscale transformation to improve the quality of the input data. Subsequently, a deep learning platform was employed with three different advanced types of convolutional layers for efficient feature extraction and accurate iris classification.

The principal findings of the research conducted can be generalized in the following way:

- Using Inpainting and CLAHE as a way of reducing specular reflections and ensuring overall improvement in quality and contrast of the iris images in general, thus, improving the reliability of proceeding operations.
- Development of the image of the eye using HoughCircles algorithm to be able to obtain a precise and effective segmentation of the iris region of the eye.
- The process of designing and implementation of a framework of deep learning model with multiple convolutional layers, which is specially designed to extract features and classify iris in a definitive manner.

2. RELATED WORK

There is a vast range of applications of the deep learning models to perform the tasks of iris detection and classification, which have demonstrated rather good accuracy on various benchmark datasets. Traditional neural networks NN and CNN have been used early where the experiment on the CASIA Iris-V1 dataset produces good results of 95.5 and 95 percent accuracy, respectively [25]. SwinIris framework built on a Swin Transformer architecture led to high accuracy in its operations of approximately 95.14 percent to 99.56 percent on various data sets such as CASIA-Iris-Thousand and CASIA-Iris-Lamp, CASIA-IntervalV4 and CASIA-IntervalV3 [26]. The other strategy involved the fusion of CNNs and Hamming Distance HD measures to improve the robustness of classification. Such a hybrid system was tested on the datasets CASIA-Iris-Interval V4, IITD, MMU with the results being 94.88 percent, 96.56 percent and 98.01 percent respectively [27]. Also, some CNN-related models were individually trained using specialized sets, including the MMU and IIT databases and generated 95.33 [28] and 97.8 [29] accuracy rates. Higher architectures like AlexNet have been employed on a mixture of seven iris datasets that have reported high accuracy with range getting to 98.4 to 99.4 percent [30]. Also, the YOLOv4 model has been used on the CASIA-V3 dataset to have a detection accuracy of 98 per cent [31]. Moreover, the BOC-IrisNet design, an iris-specific architecture, has attained the state-of-the-art results on CASIA Iris V4, IIT, and MMU databases with the reported accuracy values being 99.75%, 99.35%, and 99.45%, respectively [32]. Nevertheless, there are still numerous caveats in the current approaches that depend more on either pre-trained models or large open-domain datasets, which are not easily transferable to different acquisition modes. There is also the problem that some of the proposed architectures are complex to the degree that it increases the computational overhead and therefore makes it hard to implement the architectures practically.

3. THE PROPOSED METHODS

The following section offers about the methodology in the proposed approach to classifying iris. The whole procedure is organized according to the two key phases: (1) Preprocessing and Iris Segmentation, it will enhance the iris picture and isolate the iris area properly. (2) Feature Extraction and Classification, where useful features will be extracted out of the extracted images and then applied to consequently classify them with the help of a deep learning model.

To enhance the correctness and computational efficiency of eye image iris segmentation, a chain of higher-order image processing techniques was utilized. It begins by grayscaling the input image, then uses the CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm to locally adjust contrast, and finally the inpainting operation is performed to remove any specular reflections that could impede accurate segmentation. After applying these enhancements, the HoughCircles algorithm is then used in an attempt to automatically detect both the iris and pupil boundaries in order to segment the iris region with precision. Finally, normalize the iris to a rectangle using the Daugman approach. Fig. 1 is the complete process of the image preprocessing and segmentation steps beginning with the grayscale conversion and concluding with the normalization step.

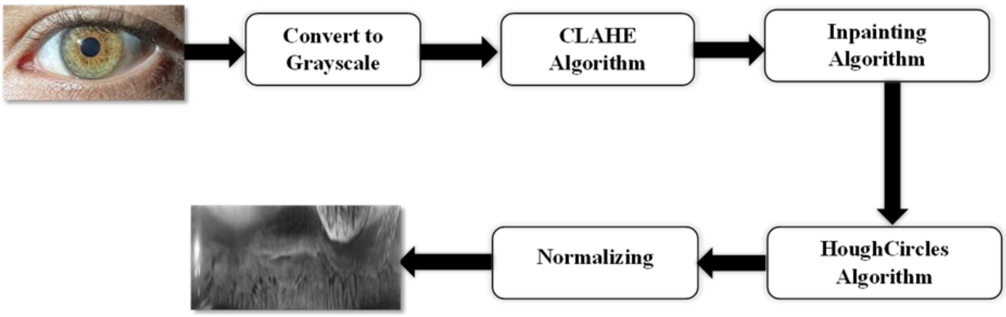

FIGURE 1. **The suggested Iris segmentation method**

The given subsection contains a detailed overview of the deep learning model that has been proposed in the present paper and that is specifically adapted to the processing of the image of iris. The architecture of the model involves the use of three different kinds of convolutional layers in order to make possible effective extraction of the features. The input layer is set to receive iris images with 360×180 in pixel resolution. The first part of the model has two standard convolutional layers. The first layer has 32 filters and there is a max pooling layer of 4×4 window size. The second convolutional layer has 16 filters and is also coupled with max pooling layer with 2 windows size of 2×2. The pooling operations are geared towards reducing size of the feature mappings whilst ensuring that the most salient feature was preserved. Thereafter, the model applies two spatial in convolutions. These are the processing carried out on the vertical axis keeping 32 filters and the second one on the horizontal axis keeping the same number of filters define them. Then, the use of a max pooling layer of the 2×2 window is initiated to further reduce the spatial dimension and preserve critical features. The third convolutional part of the model has a Depthwise Conv layer, each channel is convolved by a different filter. The resultant of these is then merged via pointwise convolution layer with 1×1 kernels. The next stage is also preceded by a max pooling layer of the size 2×2 so as to reduce the dimension and the computing burden. After the convolutional layers, there are two fully connected layers used. The goal of these layers is adaptation to the dimensions of output of the previous ones as well as the number of classes to be classified in the task of classification. The final output layer utilizes the Softmax activation function that is generally utilized in multi-class classification and is configured to provide probabilities related to the number of classes defined.

The optimal set of parameters for the proposed model was found by iterative experimentation through step-by-step adjustment of significant architecture parameters such as the number of convolutional layers, filter sizes, and pool window size. The full architectural details for the model are listed in Table 1, while a graphical representation of the structure of the model is shown in Fig. 2.

Table 1. **The proposed model building**

Type of layer	Ker. size	Ker. No.	Shape	Parameter
Input	-	-	360×180	-
Con. 1	3×3	32	358,178,32	320
Pooling 1	4×4	-	89,44,32	0
Con. 2	3×3	16	87,42,16	4624
pooling 2	2×2	-	43,21,16	0
Horizontal convolution	1×3	32	41,21,32	1568
Vertical convolution	3×1	32	41,19,32	3104
pooling 3	2×2	-	20,9,32	0
Depth. con.	3×3	1	18,7,32	320

Point. Con.	1×1	32	18,7,32	1056
pooling 4	2×2	-	9,3,32	0
Flatting layer	-	-	864	0
Fully con.	-	-	512	442880
Dropout 0.5	-	-	512	0
Fully con.	-	-	256	131,328
Dropout 0.3	-	-	256	0
Softmax	-	-	177	45489

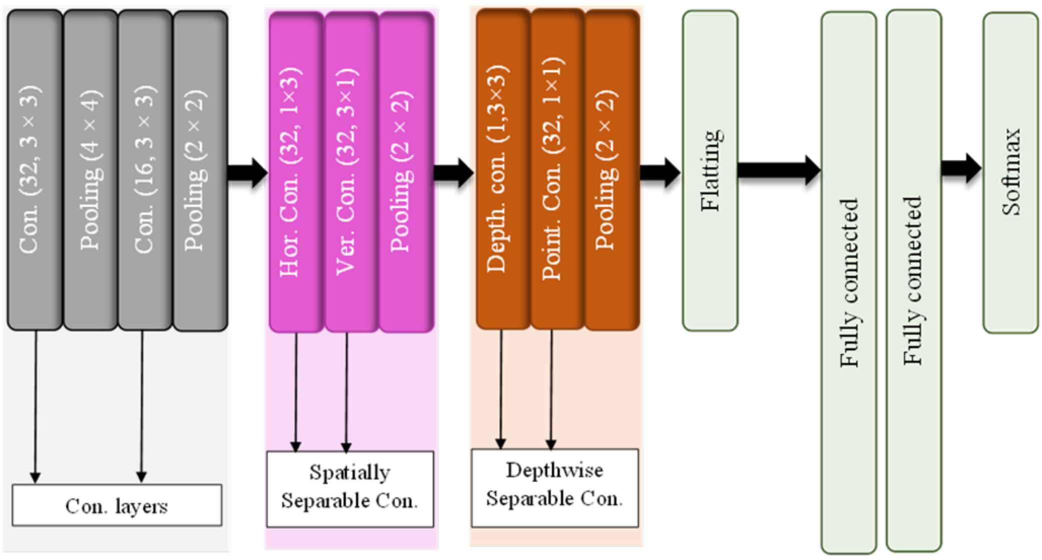

FIGURE 2. **The proposed iris method**

4. RESULTS AND DISCUSSION

The proposed approach to iris classification was implemented using Google Colab, an online cloud-based development environment for Python 3. To assess the effectiveness of the approach, experiments were conducted on the MULBv1 dataset, which was the primary resource for iris images used to train and test. System performance was measured numerically with the assistance of benchmark assessment metrics, i.e., Accuracy and F1-Score, which reveal the prediction capability of the model and the credibility of classification.

4.1 DATASET

Proposed method was experimentally evaluated using the MULBv1 dataset [33]. This dataset contains 3540 images (20 images of the right iris for each individual for 177 people) with photos taken when the light is different. The micro camera of the iPhone 14 pro max was used to take the pictures of the iris, and a distance of about 2- 5 centimeters between the camera and the eye was used to take photos irrespective of the clarity and consistency of the images used. Fig. 3 shows representative samples of the dataset, which suggests the variety and quality of the pictures of iris grabbed.

FIGURE 3. **Samples of Iris images**

4.2 SEGMENTATION RESULTS

Section 3.1 described the procedure for segmenting the iris region from full eye images and enhancing their visual quality. Both steps of segmentation and resolution enhancement were included in the process to prepare the images for analysis. Fig. 4 presents steps of the images acquired after enhancement and segmentation processes, demonstrating the effectiveness of the proposed preprocessing approach.

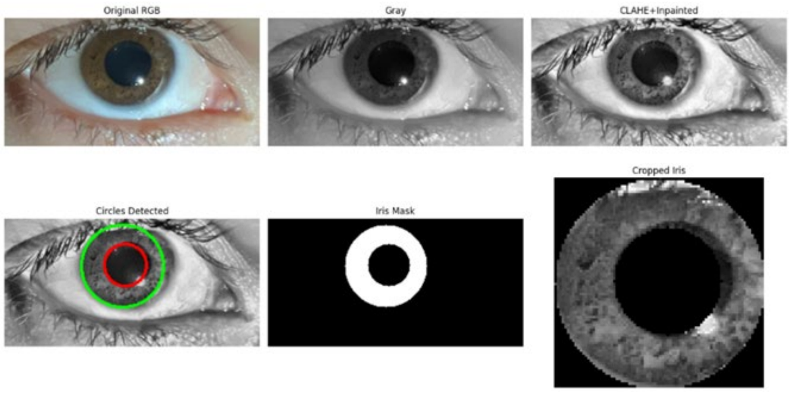

FIGURE 4. **Segmentation Steps**

Before being passed into model, the iris images undergo a proprietary type of normalization, specialized for the purpose of iris recognition. Unlike common normalization procedures that usually involve pixel intensity scaling, normalization in iris refers to geometric transformation of the segmented iris boundary from the original annular (ring-shaped) form into rectangular representation. This operation is often used using the Daugman model, where every point in the iris area is mapped according to its polar coordinates with respect to the iris and pupil boundaries. This yields a dimensionally normalized rectangular image with the texture patterns of the iris maintained while the scale, rotation, and dilation changes of the pupil are eliminated. Following normalization, the resulting iris images are then resized to a fixed resolution 360 × 180 pixels to match the input size as defined by the deep learning model. These processes offer both spatial coherence and invariance, and they further enhance the ability of the model to learn robust and discriminative features. Fig. 5 shows representative samples of the iris normalization.

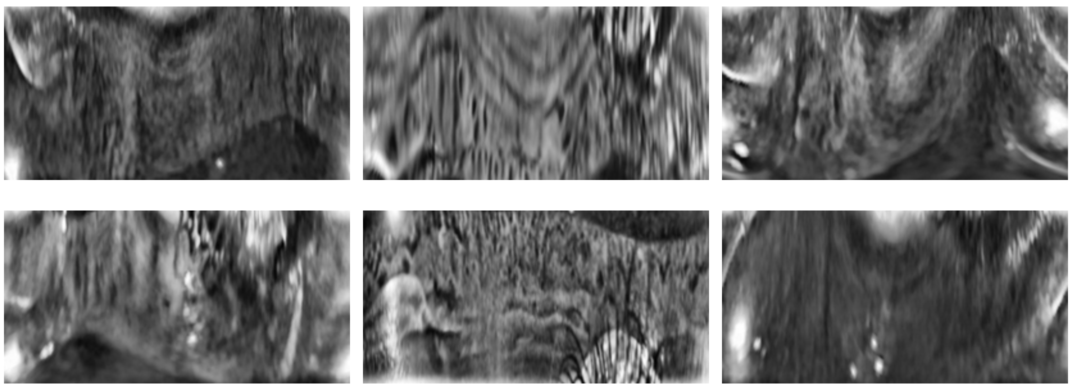

FIGURE 5. **Samples of Iris normalization**

4.3 EVALUATING THE SUGGEST TECHNIQUE'S PERFORMANCE

Two main evaluation measurements were applied to determine the effectiveness of the suggested technique in this research project: Accuracy and F1-Score. Accuracy, measuring the overall accuracy of how the model makes its predictions is formally defined as in Equation (1).

$$Acc = \frac{True\_Pos. + True\_Neg.}{True\_Pos. + True\_Neg. + False\_Pos + True\_Neg} \tag{1}$$

True Pos. is the number of times iris were identified and classified correctly. While True Neg. is the number of times iris were weeded out correctly. On the other hand, False Pos. is the number of times iris were incorrectly classified as correct, while False Neg. is the number of times iris were mis weeded out as incorrect.

The F1Score is the harmonic mean of Precision (Pre) and Recall (Rec), and in general a balanced measure of false positives and false negatives. It is calculated out to be Equation (2). The two elementary measures by namely Precision and Recall are mathematically specified as Equations (3) and (4) respectively.

$$F1 = \frac{2 \times Pre. \times Rec.}{Pre. \times Rec.} \tag{2}$$

$$Pre. = \frac{True\_pos.}{True\_pos. + False\_pos.} \tag{3}$$

$$Rec. = \frac{True\_pos.}{True\_pos. + False\_Neg.} \tag{4}$$

Following the preprocessing and segmentation procedures applied to the dataset, the data were partitioned into two subsets: 80% allocated for training and 20% reserved for testing. The model was developed using Keras, a widely adopted deep learning framework. During the training phase, the convolutional layers were initialized using the Leaky ReLU activation function, which is an enhanced variant of the traditional ReLU, designed to address issues such as the "dying ReLU" problem. To optimize the model's parameters during training, the Adam optimizer was employed with a fixed learning rate of 0.001. The training process was executed over 200 epochs, allowing the model to iteratively adjust its internal parameters and progressively enhance its predictive capabilities. A series of experiments were conducted to fine-tune the model architecture and hyperparameters. These experiments involved systematic modifications to key components such as the number of convolutional layers, the number of filters, and the activation functions used. Each experiment aimed to identify the configurations that yield the best classification performance. As a result of this optimization process, the proposed model achieved a classification accuracy of 98.21% and an F1 score of 98.15%, indicating its high effectiveness. Table 2 presents a comparative evaluation of different model configurations, demonstrating the impact of varying individual parameters while keeping others constant.

Table 2. The performance results of assessing the suggest technique

Con.1	Con.2	Hor. con.	Ver. con.	Depth. Con.	Point. Con.	Accuracy	F1_score
32(3×3)	16(3×3)	-	-	-	-	91.43	90.87
64(3×3)	32(3×)	-	-	-	-	90.13	89.65
32(3×3)	16(3×3)	32(1×3)	32(3×1)	-	-	95.71	95.11
32(3×3)	16(3×3)	64(1×3)	64(3×1)	-	-	94.92	94.9
32(3×3)	16(3×3)	32(1×3)	32(3×1)	(3×3)	64(1×1)	97.01	96.53
32(3×3)	**16(3×3)**	**32(1×3)**	**32(3×1)**	**(3×3)**	**32(1×1)**	**98.21**	**98.16**

Fig. 6 illustrates the progression of the proposed model's accuracy with respect to the number of training iterations. During the initial epochs, there is a noticeable and rapid improvement in accuracy, indicating the model's ability to efficiently capture fundamental patterns within the dataset. As the training advances beyond epoch 25, the rate of improvement begins to decline, reflecting the model's shift from learning basic structures to refining its understanding of more intricate and detailed features. Approaching epoch 160, the accuracy curve begins to plateau, suggesting that the model has entered a saturation phase. This stabilization in accuracy signifies that the model has achieved an optimal balance between learning from the training data and maintaining generalization, thereby minimizing the risk of overfitting.

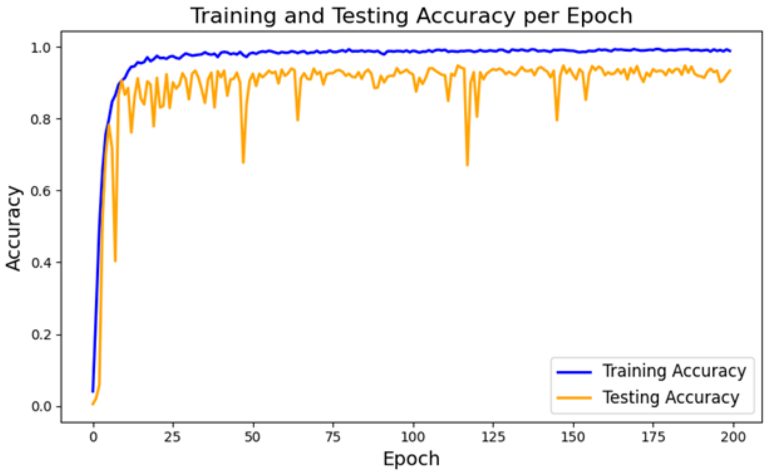

FIGURE 6. Accuracy of the proposed model

Fig. 7 presents the relationship between the number of training iterations and the loss values computed using the Categorical Crossentropy function, which was employed as the loss function in the proposed model. In the initial stages of training, the loss values exhibit noticeable fluctuations and instability. This behavior reflects the model's ongoing adjustments to its internal weights as it attempts to adapt to diverse patterns within the data. As training progresses, particularly beyond epoch 160, the loss function begins to stabilize gradually. This stabilization indicates that the model has become more proficient in representing the data and minimizing prediction errors. Eventually, the loss values converge within a narrow range between 0.05 and 0.08, signifying that the model has entered a phase of consistent learning with minimal error, and that further improvements in performance become marginal.

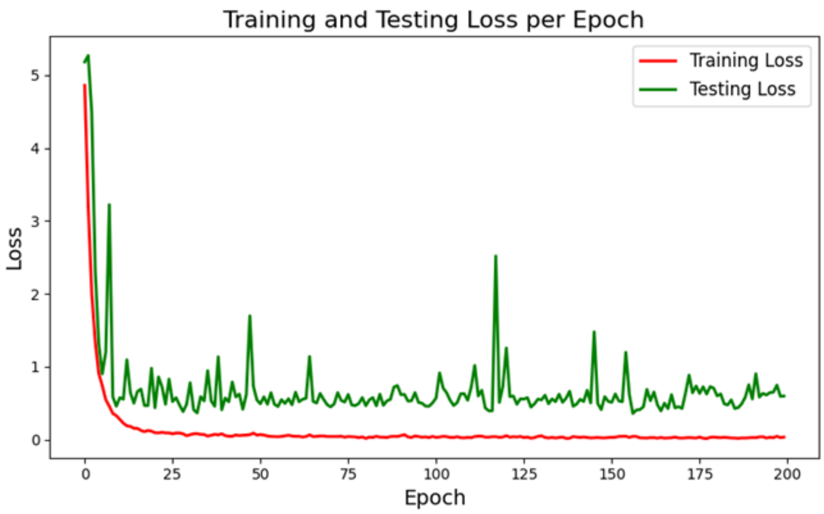

FIGURE 7. Loss function of the proposed model

4.4 THE FEATURES MAPS TECHNIQUE

To assess and interpret the model’s behavior, the feature maps approach was employed. This technique provides valuable insight into how the model learns and applies various filters, as well as how data representations evolve across different layers of the network. Generally, feature maps generated by layers closer to the input capture fine-grained and localized features, whereas those near the output layer tend to represent more abstract and high-level characteristics. Fig. 8 illustrates the visualized feature maps from the second convolutional layer, which comprises 16 filters. As observed, each filter extracts a distinct type of feature from the input, highlighting the diversity in feature representation learned at this stage.

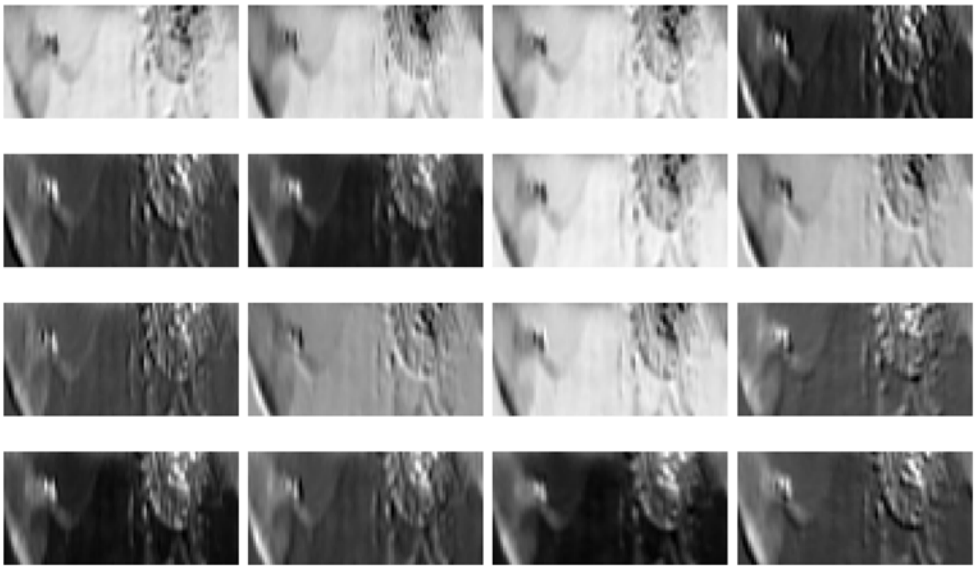

FIGURE 8. **Feature maps for standard convolution layers**

Similarly, Fig. 9 presents selected feature maps (16 out of 32) from the depthwise convolution layer. At this deeper level of the network, the extracted features appear less interpretable to the human eye, reflecting the model's shift toward more abstract representations. Despite their reduced visual interpretability, these deeper features are highly informative for the classification process. This progression aligns with expectations in convolutional architectures, where increasing depth enhances the model's capacity to extract semantically rich information.

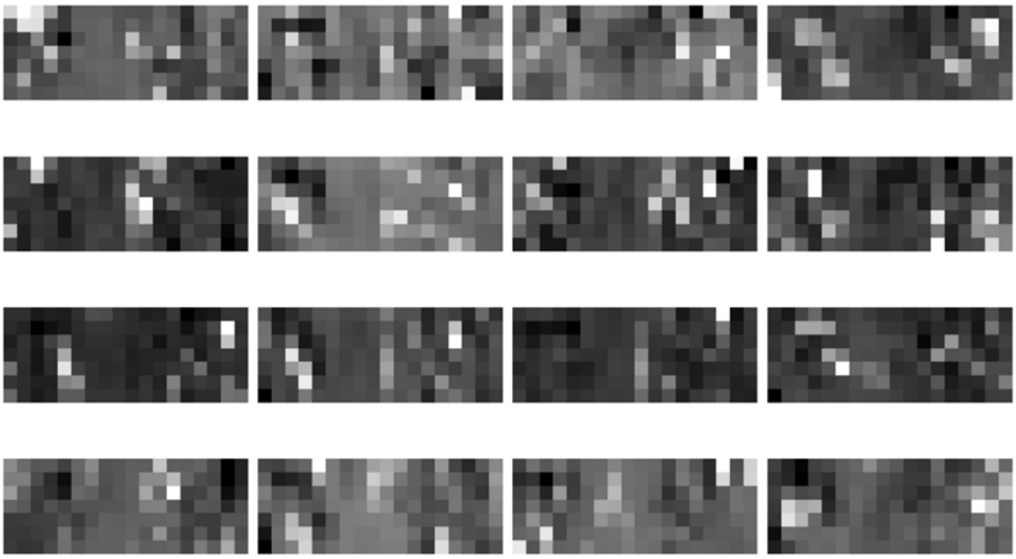

FIGURE 9. **Feature maps for depth convolutions layers**

4.5 DISCUSSION

Despite the inherent challenges associated with variations in image resolution, diversity in iris shapes and sizes, limited data availability, and fluctuations in lighting conditions, the outcomes achieved through the proposed approach have demonstrated notable effectiveness. The results reflect the adoption of a structured methodology for constructing a model composed of multiple convolutional layers, preceded by essential preprocessing steps such as image enhancement and segmentation. These preparatory phases significantly contributed to the model's robust and reliable performance. Unlike previous studies [25,26,28], which heavily relied on large-scale datasets, the proposed method attained high performance even with less dataset. Moreover, in comparison with standard CNN architectures employed in earlier works [30,31], the model introduced in this study was explicitly tailored to address the distinctive challenges associated with iris classification tasks. Additionally, models presented in studies such as [27,32] tend to exhibit greater computational complexity, whereas the proposed model offers a more efficient alternative with reduced computational demands. A comparative evaluation of the methodologies and their respective results is summarized in Table 3.

Table3. Comparison of the proposed model performance and the related works

Reference	Technique	Dataset	Accuracy %
[25]	NN, CNN	CASIA Iris-V1	95.5, 95
[26]	SwinIris	CASIA-Iris- Thousand	99.56
		CASIA-Iris-Lamp	99.17
		CASIA-IntervalV4	95.83
		CASIA- IntervalV3	95.14
[27]	CNN and HD	CASIA-Iris-Interval V4	94.88
		IITD	96.56
		MMU	98.01
[28]	CNN	MMU	95.33
[31]	YOLOV4	CASIA-v3	98
[32]	BOC-IrisNet	CASIA Iris V4	99.75
		IIT	99.35
		MMU	99.45
[30]	Alexnet	CASIA V-4	99.1
The proposed Method	Multi-Type Con. Network	MULBv1	98.21

5. CONCLUSIONS

This paper introduced a robust and efficient iris recognition system that combines traditional image processing techniques with a novel multitype convolutional neural network architecture. The proposed approach eliminates significant difficulties in iris detection and classification, including those introduced by image quality, specularities, and the complex texture of the iris. The segmentation method employed contrast enhancement via CLAHE, reflection removal via inpainting, and HoughCircles for precise iris localization. Preprocessing was significant in enhancing input image quality, leading to better segmentation and normalization results. In the process of classification, the structure of the multitype convolutional network—employing standard, spatial, and depthwise convolution layers—enabled the delivery of deep and discriminative features from normalized iris images. Experimental evaluation on the MULBv1 dataset proved that the proposed method was very effective with an accuracy of 98.21% and a respective F1-score of 98.16%, much better than several state-of-the-art models, yet computationally efficient. This comparative analysis proved that despite a small and heterogeneous dataset, the model performs quite competitively, pointing out its possible application in real-world biometrics. Future work can include extending the model to enable cross-spectral iris recognition tasks, such as other biometric modalities, and continued optimization of the model for use on low-resource devices.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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