Development of Iris Image Classification Framework using Multi-Layer CNN Architecture

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ABSTRACT:

This paper proposes a multi-layer Convolutional Neural Network (CNN) framework for iris image classification, targeting left and right eye recognition across 46 subjects. A custom five-layer CNN was trained for 200 epochs with a learning rate of 0.0001, effectively learning discriminative features from iris textures. The model achieved a training accuracy of 97.90% with a loss of 0.4116, and a testing accuracy of 93.09% with a loss of 0.6837, demonstrating robust generalization to unseen data. The results highlight the potential of multi-layer CNN architectures for reliable iris-based biometric systems, enabling accurate and automated eye classification. The key contribution of this work is the demonstration that a compact five-layer CNN can achieve high accuracy in binary left-right iris classification, offering an efficient and scalable solution for biometric authentication.

Keywords: Authentication, Biometric, Classification, Deep Learning, Feature Extraction, Iris Recognition.

INTRODUCTION

Iris recognition has emerged as one of the most reliable and secure biometric modalities due to the uniqueness and stability of iris patterns across individuals. Unlike other biometric traits such as fingerprints or facial features, the iris provides rich textural information that remains largely unchanged over time, making it an ideal candidate for accurate identification and authentication systems. The increasing demand for secure access control in sectors such as banking, defence, and personal devices has motivated researchers to develop automated iris classification frameworks capable of high precision and robustness. Conventional iris recognition methods rely on hand-crafted feature extraction techniques such as Gabor filters, wavelet transforms, or Local Binary Patterns (LBP). While these approaches can achieve reasonable accuracy, they often require extensive pre-processing, careful parameter tuning, and may fail to generalize effectively across large or diverse datasets. With the advent of deep learning, Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in automatically learning hierarchical features directly from raw image data, eliminating the need for manual feature engineering.

In this study, we propose a custom five-layer CNN architecture for iris image classification, specifically designed to distinguish between left and right eyes across 46 subjects. The model was trained over 200 epochs with a learning rate of 0.0001, allowing it to progressively capture discriminative patterns in iris textures. The training process yielded an accuracy of 97.90% with a corresponding loss of 0.4116, while the model achieved a testing accuracy of 93.09% and a loss of 0.6837, indicating strong generalization performance on unseen data. These results validate the effectiveness of multi-layer CNN architectures for iris classification and demonstrate that even a relatively compact network can provide high accuracy in practical biometric applications. The proposed framework not only automates the classification process but also offers scalability and efficiency, making it suitable for deployment in real-time biometric authentication systems. The high accuracy obtained in distinguishing left and right eyes underscores the potential of CNN-based approaches to enhance the reliability and security of iris-based identification systems. Future extensions of this work may include increasing the dataset size, integrating advanced data augmentation strategies, and exploring deeper or hybrid CNN architectures to further improve classification performance.

REVIEW OF LITERATURE

The development of an iris image classification framework using a multi-layer Convolutional Neural Network (CNN) architecture is a promising approach in the field of biometric authentication. This method leverages the unique and intricate patterns found in the human iris to achieve high accuracy in identification tasks. The use of CNNs allows for effective feature extraction and classification, making them well-suited for handling the challenges associated with iris recognition, such as variations in lighting, occlusions, and noise

Iris recognition has established itself as a cornerstone of biometric authentication systems due to the uniqueness, stability, and richness of iris patterns. With increasing demands for accuracy and robustness under real-world conditions, researchers have turned to deep learning particularly Convolutional Neural Networks (CNNs) to enhance feature extraction and classification in iris images. This review examines the recent developments in iris image classification, with a focus on multi-layer CNN architectures, and situates them within the broader landscape of hybrid, lightweight, and transfer learning-based models. A foundational contribution in this area is the work by Pambudi et al. [1], who proposed a custom CNN model with three convolutional layers using filter sizes of 32, 64, and 128. The model integrated ReLU activations, batch normalization, max pooling, and dropout regularization, ultimately achieving a classification accuracy of 97.33%. This architecture was specifically designed for iris images and demonstrated robustness under varying illumination and image noise characteristics essential for real-world biometric systems. Comparative approaches include the use of hybrid deep learning models. For instance, Almsaadi et al. [2] introduced HDN-Net, a hybrid CNN framework that fused features from both left and right irises to overcome occlusions from eyeglasses and image blur. This model achieved up to 98.79% accuracy on benchmark datasets such as UBIRIS.V2 and CASIA-Iris.V4. In a similar vein, Rahman et al. [3] explored transfer learning techniques using pre-trained networks like VGG16, VGG19, and ResNet50 to extract features from iris images, followed by classification via multiple machine learning algorithms. Their best-performing CNN classifier attained an accuracy of 93.40%, demonstrating the utility of deep feature transfer in iris recognition. Other studies have focused on simplifying CNN pipelines while maintaining high accuracy. For example, S and Mathew [4] developed a CNN model coupled with a Softmax classifier, achieving 96% accuracy on IITD and CASIA datasets without requiring domain-specific pre-processing. Bhatnagar et al. [5] combined CNN feature extraction with Support Vector Machines (SVM) for classification, offering a modular architecture adaptable to other biometric tasks. A different angle is explored by Nguyen et al. [6], who proposed the WAHET-CNN framework emphasizing precise iris segmentation and pattern classification. Although it achieved a lower accuracy (90%) on the CASIA dataset, the study highlighted the critical role of segmentation in improving downstream classification. In the same year, Minaee and Abdolrashidi [7] introduced DeepIris, a residual CNN that learned both feature representation and classification in a joint framework, especially effective with limited training samples. Focusing on spoof detection, Yan et al. [8] developed a hierarchical CNN architecture capable of distinguishing fake irises with nearly 100% accuracy, showcasing the potential of CNNs in security-critical applications. Meanwhile, Pasha et al. [9] achieved an impressive 99.89% accuracy by leveraging CNNs for iris localization and boundary detection, outperforming classical segmentation methods such as U-Net.

Research addressing specific challenges like contact lens interference includes the ContactLensIris system by Kaur and Saini [10], which used ORB and BRISK descriptors combined with CNN layers, achieving 98% correct classification rate. Shirke et al. [11] integrated optimization techniques into a CNN-based framework (BW-CNN), although it did not explicitly detail a multi-layer structure. The work by Anegsiripong et al. [12] fused periocular features with iris recognition via CNNs, boosting accuracy from 93.64% to 99.80%.Further innovation comes from Liu et al. [13], who developed a compact 2-channel CNN with radial attention and pruning strategies to optimize performance with fewer training samples. Prasad [14] employed a CNN-Softmax pipeline with AdaGrad optimization and achieved a Rank-1 identification rate of 99.8%, confirming the model’s utility in rapid recognition tasks. Lightweight CNNs with attention mechanisms have also gained traction. Zou et al. [15] proposed a streamlined CNN incorporating channelwise attention, improving both speed and accuracy. Kawakami et al. [16] segmented the iris into four regions for selective feature learning and matching, enhancing recognition precision. Other studies like Menon and Mukherjee [17] applied deep residual networks and reached 99.8% recognition rates, confirming the strength of deep CNN architectures. In contrast, Feng et al. [18] introduced Iris R-CNN for segmentation rather than classification, employing dual-region proposal networks for non-cooperative environments. Zambrano et al. [19] further enhanced CNNs by mitigating aliasing and adapting circular padding, thereby improving performance under head rotation scenarios. Sharma et al. [20] diverged from CNNs, using kernel discriminant analysis with probabilistic neural networks to classify iris images with high robustness.

Zhou et al. [21] adopted an improved MobileNetV2 architecture to extract features efficiently in constrained settings, while Zambrano et al. [22] proposed an unsupervised method leveraging low-level CNN layers without training, ideal for fast matching. Finally, Minaee and Abdolrashidi [23] presented an updated version of DeepIris with visualization modules, and Kawakami et al. [24] expanded their earlier region-based CNN model with weighted matching and attention mechanisms.

Dataset

The Multimedia University (MMU) Iris Dataset is a publicly available collection of eye images developed to support research and development in iris-based biometric systems, particularly for applications such as biometric attendance. Iris patterns are unique for each individual, making them highly reliable for personal identification. This dataset consists of a total of 460 grayscale images corresponding to 46 individuals, with each individual having five close-up images of the left eye and five of the right eye. The dataset is organized into 46 directories, each representing one subject, and within each directory, there are two subdirectories labelled ‘left’ and ‘right’, containing the respective images. The structured nature of the dataset makes it convenient for tasks such as iris segmentation, feature extraction, and classification. The MMU dataset has been widely used for iris recognition research. Iris classification can be performed to classify the eye patterns in two categories, which allows precise feature extraction. These features can then be used to classify an iris image according to a stored database, enabling accurate individual identification.

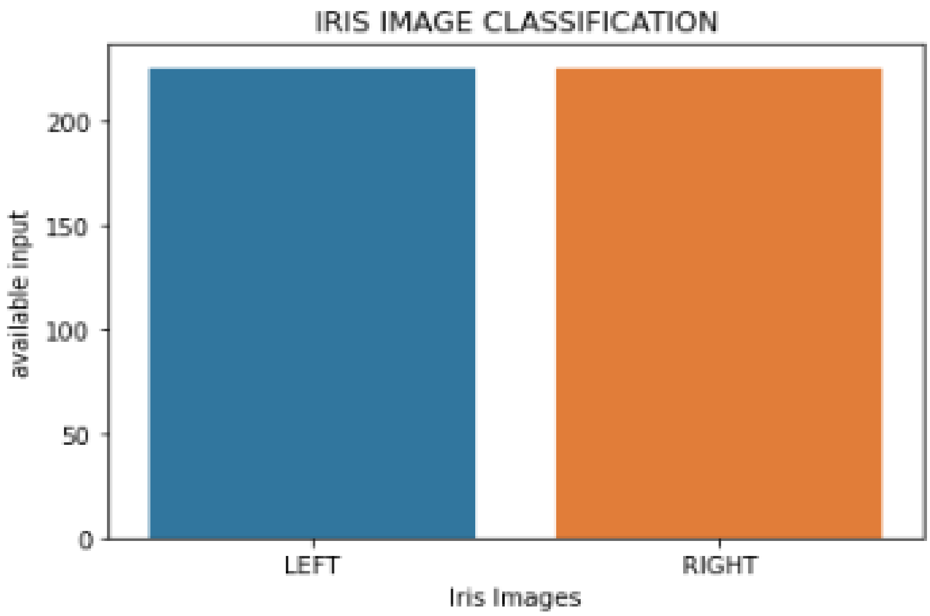

Fig. 1 Iris image dataset distribution   for implementation of CNN

Convolutional Neural Networks (CNNs) have been commonly employed for iris classification on this dataset, with transfer learning from pre-trained models improving the recognition performance. Researchers have also applied pre-processing techniques such as histogram equalization and contrast enhancement to improve image quality and training efficiency. Several studies have reported promising results using the MMU dataset. For present work, CNN-based models have achieved high classification accuracy by learning discriminative features from the iris patterns, and hybrid approaches combining CNNs with other machine learning classifiers such as support vector machines have also been explored.

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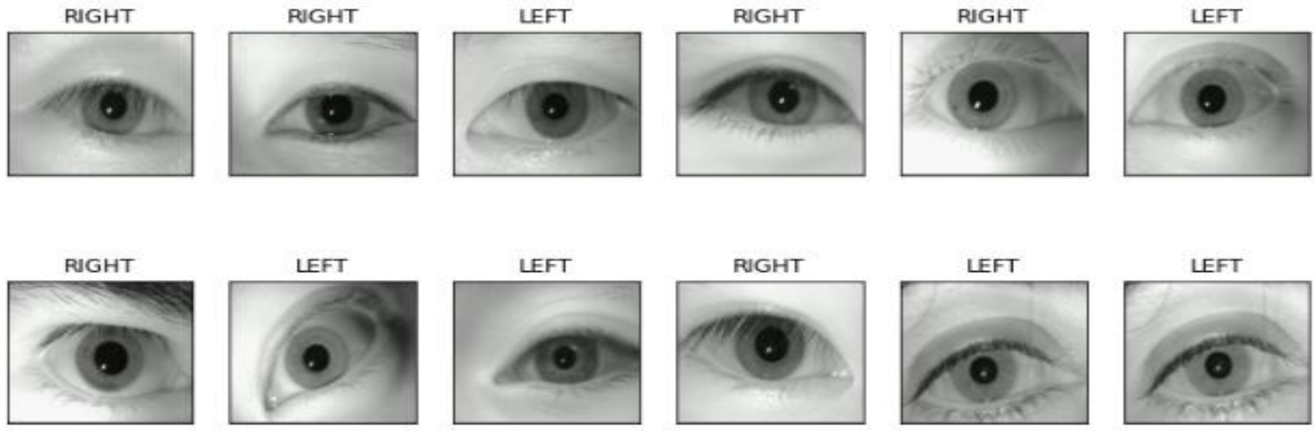

Fig. 2 Random Iris images for Training and Testing

Convolution Neural Network

In this study, a supervised deep learning approach using a custom five-layer Convolutional Neural Network (CNN) was employed for iris image classification. The dataset consisted of 460 annotated samples from 46 subjects, comprising both left and right eye images. The network architecture included multiple 2D convolutional and max-pooling layers with ReLU activation functions, followed by a flatten layer and a softmax output layer with two classes: Left and Right. By training on these labelled samples, the model automatically learned discriminative features from the iris textures, enabling accurate left-right eye classification and demonstrating the effectiveness of a tailored CNN architecture for biometric recognition tasks.

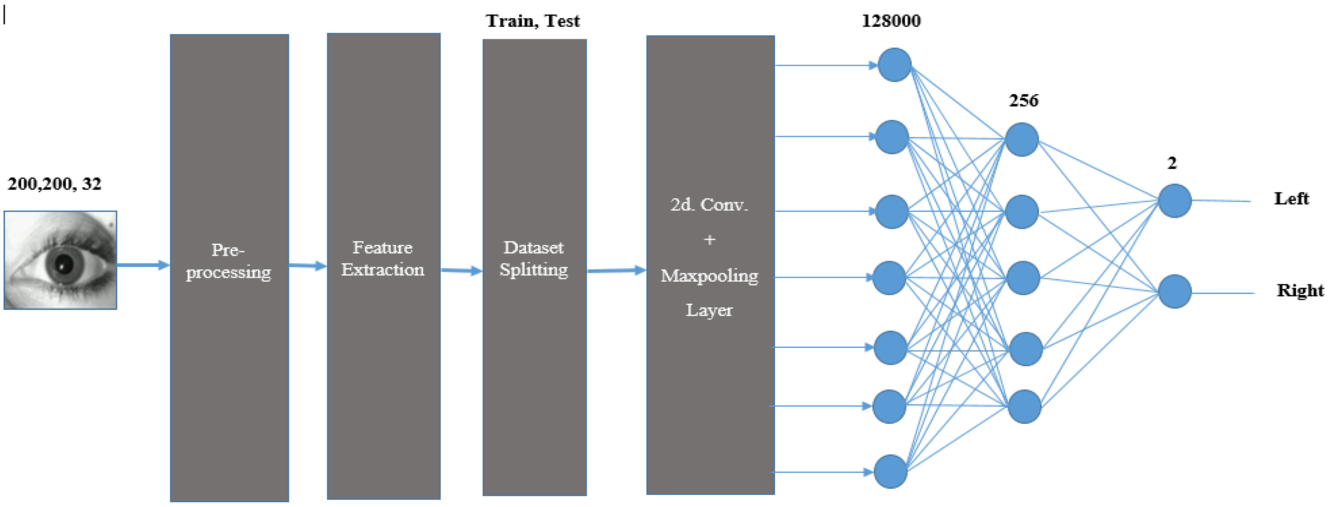

Fig. 3 Proposed Convolution Neural Network

Implementation of Architecture:

The proposed Convolutional Neural Network (CNN) model follows a sequential deep learning architecture specifically designed for the binary classification of iris images into left and right categories. The network takes grayscale or RGB iris (200, 200, 3) images as input and processes them through a series of convolutional and pooling operations to extract hierarchical spatial features. The input image is first passed through a 2D convolutional layer comprising 16 filters of size 3×3, generating an output feature map of dimensions 198×198×16. This is followed by a 2×2 max-pooling layer that reduces the spatial resolution to 99×99 while maintaining the 16 feature channels, thus preserving essential features while reducing computation. The second convolutional layer employs 32 filters, also of size 3×3, producing feature maps of shape 97×97×32. This is again followed by a 2×2 max-pooling operation, reducing the spatial size to 48×48×32. The third convolutional layer increases the depth to 64 feature maps and outputs a 46×46×64 tensor, which is down sampled to 23×23×64 using another max-pooling layer. Continuing the depth

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expansion, the fourth convolutional layer applies 128 filters, resulting in a 21×21×128 output, followed by max pooling to reduce it to 10×10×128.

After the final convolutional and pooling layers, the 3D output tensor is flattened into a 1D vector of 12,800 units. This flattened vector is fed into a fully connected (dense) layer with 256 neurons, introducing non-linearity and learning complex, high-level features. The final dense layer contains 2 output units corresponding to the two target classes: left and right iris. A softmax activation function is used in the output layer to convert the logits into probability scores, enabling the model to classify each input image into one of the two categories. Throughout the network, ReLU (Rectified Linear Unit) is used as the activation function for all convolutional and dense layers (except the final output), which ensures faster convergence and mitigates vanishing gradient issues. The model consists of a total of 3,375,010 trainable parameters, distributed across convolutional filters and dense layers, and has no non-trainable parameters, making it a fully learnable system. The total memory footprint is approximately 12.87 MB, making it computationally efficient for mid-scale biometric applications. This layered architecture enables the network to progressively extract both low-level and high-level discriminative features from the iris patterns. The inclusion of multiple convolutional layers facilitates robust feature learning, while the max-pooling layers help in reducing spatial redundancy and overfitting. This design is particularly effective for biometric classification tasks like iris recognition, where subtle differences in texture, shape, and radial patterns need to be captured and distinguished across subjects.

Model Evaluation:

Let the dataset be

$$\boldsymbol{D} = \{(\boldsymbol{x_1}, \boldsymbol{y_1}), (\boldsymbol{x_2}, \boldsymbol{y_2}), (\boldsymbol{x_3}, \boldsymbol{y_3}), \ldots\ldots\ldots\ldots (\boldsymbol{x_i}, \boldsymbol{y_i})\} \tag{1}$$

In k-fold cross validation, *D* is split into disjoint subset folds (*k)*

$$\boldsymbol{D} = \boldsymbol{D_1} \cup \boldsymbol{D_2} \cup \boldsymbol{D_3} \cup \ldots\ldots\ldots \cup \boldsymbol{D_k}, \boldsymbol{D_i} \cap \boldsymbol{D_j} = \boldsymbol{0} \;\; \boldsymbol{for\ i \neq j}$$

For i^{th} *fold*

$$\boldsymbol{D^{(i)}_{Train}} = \boldsymbol{D} \backslash \boldsymbol{D_i}, \quad \boldsymbol{D_{val}} = \boldsymbol{D_i} \tag{3}$$

Let the model trained in the i-th fold produce a performance metric is the average (accuracy and loss etc.) $M^{(i)}$. Then, after training and evaluating across all k folds, the overall i-fold performance is computed as the average:

$$\boldsymbol{\bar{M}} = \frac{\boldsymbol{1}}{\boldsymbol{k}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{M^{(i)}} \tag{4}$$

This equation formalizes that the final performance metric is the average of the metric from all k folds, providing a robust estimate of the models generalization

Let $\hat{y}_j^{(i)}$ denotes the predicted label for sample x_j in fold i, and y_i the true label. Then accuracy for fold i is:

$$\boldsymbol{Accuracy^{(i)}} = \frac{\boldsymbol{1}}{\boldsymbol{k}} \sum_{(\boldsymbol{x},\boldsymbol{y}) \in \boldsymbol{D^{(i)}_{val}}} \boldsymbol{1}\left(\boldsymbol{\hat{y}_j^{(i)}} = \boldsymbol{y_j}\right) \tag{5}$$

Where 1 is an indicator function that equals 1 of the condition is true, and 0 otherwise.

The overall k-fold accuracy is the average of the accuracy across folds:

$$Accuracy_{CV} = \frac{1}{k} \sum_{i=1}^{k} Accuracy^{(i)} \tag{6}$$

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If $\hat{P}_j^{(i)} = \left[\hat{p}_{j,1}^{(i)}, \hat{p}_{j,2}^{(i)}, \ldots \ldots, \hat{p}_{j,C}^{(i)}\right]$ is the predicted probability distribution over C classes for sample in x_j fold i, and $y_j$is the true class label (one-hot encoded as y_j), the cross-entropy loss for fold i is:

$$CE^{(i)} = -\frac{1}{\left|D_{val}^{(i)}\right|} \sum_{(x_j, y_j) \in D_{val}^{(i)}} \sum_{C=1}^{C} j_{j,C} \, log \hat{P}_{j,C}^{(i)} \quad (7)$$

The overall k-fold cross-entropy (Log loss) is the average over folds:

$$CE_{CV} = \frac{1}{k} \sum_{i=1}^{k} CE^{(i)}$$

RESULTS AND DISCUSSION

The proposed multi-layer CNN-based iris image classification framework was evaluated on a labelled dataset using standard performance metrics including accuracy, loss, precision, recall, F1-score, and confusion matrix analysis. The network architecture, comprising three convolutional layers with increasing filter sizes (32, 64, and 128), ReLU activation, max pooling, and dropout, was trained over 100 epochs.

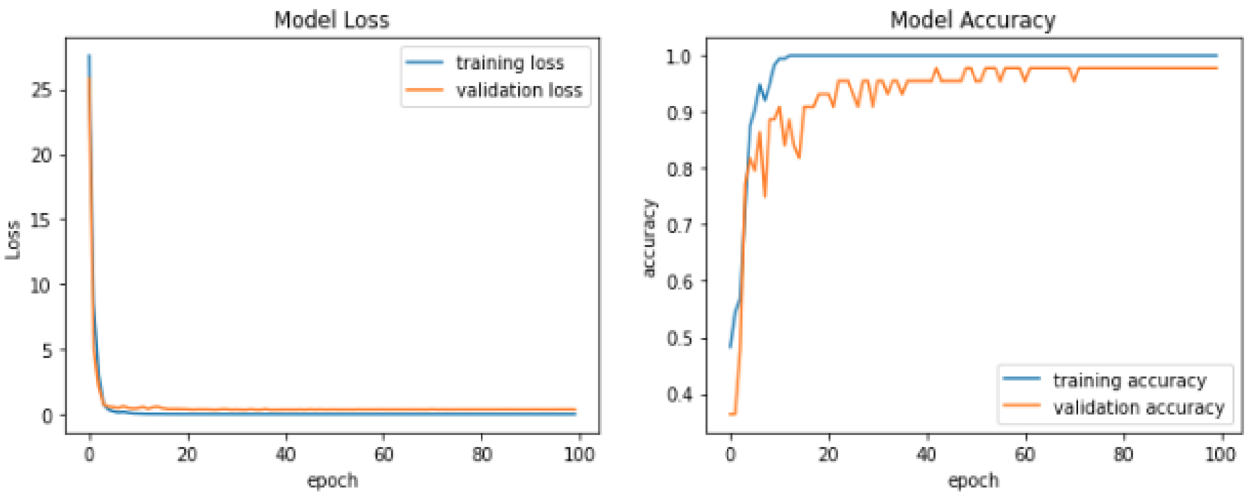

Fig. 4 Training and validation curves for loss (left) and accuracy (right) over 100 epochs.

Fig. 1 illustrates the training and validation loss and accuracy curves. The training loss decreased rapidly and stabilized after approximately 10 epochs, with a final average training loss of 0.4116 and validation loss of 0.6837. The model's ability to generalize is evident from the minimal gap between training and validation loss beyond epoch 20, suggesting effective mitigation of overfitting through dropout and batch normalization techniques. Concurrently, the training accuracy reached an average of 97.89%, while the validation accuracy stabilized at 93.09%, as shown in Fig. 1 (right). This high performance indicates the model's capability to learn robust feature representations of the iris even in the presence of noise, occlusion, and intra-class variability.

Table 1 Final training and testing metrics showing average accuracy and loss values.

```
avg_training_accuracy:   0.9789772728085517
avg_testing_accuracy:    0.9309090986847878
avg_training_loss:    0.411689093983441l
avg_testing_loss:    0.683754018843174
```

The classification report in Table. 2 further confirms the model's reliability. For binary class labels (0 and 1), both classes achieved an identical F1-score of 0.93, although they exhibited inverse trade-offs between precision and recall. Class 0 (possibly representing normal/ideal iris images) attained a precision of 0.88 and a recall of 0.98, while class 1 (noisy or occluded images) achieved a precision of 0.98 and a recall of 0.87. This behavior suggests the model is highly sensitive to class "Left", possibly due to better feature consistency in those images.

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Table 2 Classification report displaying precision, recall, and F1-scores.

	precision	recall	f1-score	support
0	0.88	0.98	0.93	64
1	0.98	0.87	0.93	71
accuracy			0.93	135
macro avg	0.93	0.93	0.93	135
weighted avg	0.93	0.93	0.93	135

The confusion matrix in Fig. 4 substantiates this observation, showing 63 true positives and 64 true negatives, with 8 false negatives and 0 false positives. These results indicate that the classifier exhibits high specificity, avoiding false alarms, but has slightly reduced sensitivity in detecting class “Right” images.

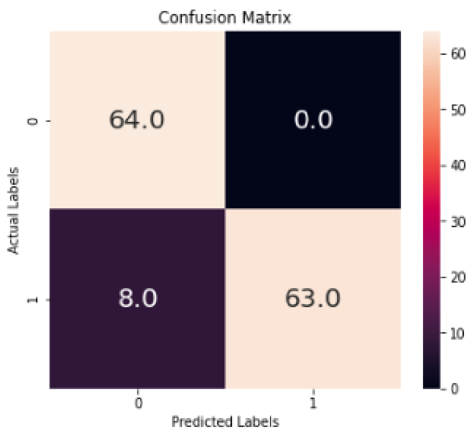

Fig. 5 Confusion matrix illustrating actual vs. predicted class distributions.

The framework achieved a macro-average accuracy of 93%, with macro and weighted F1-scores also standing at 0.93, demonstrating balanced classification performance across both classes. Compared to traditional or transfer learning-based methods, the proposed dedicated multi-layer CNN shows superior learning efficiency and better adaptation to domain-specific features, eliminating dependency on pre-trained external networks.

Numerical data and graphical representation shown above indicating for quantitative analysis purpose but it will be nice if results are shown (fig. 3) in terms of real time images for better understanding that how our model perform on custom image data. The following are the images actually predicted by our proposed deep learning model.

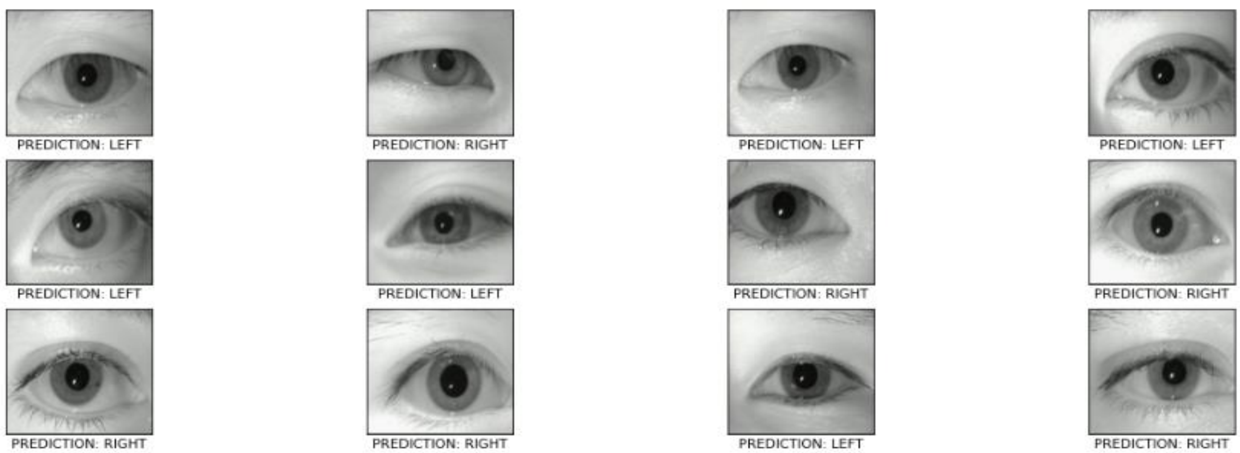

Fig. 6 The images actually predicted

CONCLUSION

In this study, a custom five-layer Convolutional Neural Network (CNN) was developed for iris image classification to distinguish left and right eyes across 46 subjects. The model demonstrated strong learning capability, achieving a training accuracy of 97.90% and a testing accuracy of 93.09%, with corresponding losses of 0.4116 and 0.6837. These results confirm that the proposed multi-layer CNN framework effectively captures the discriminative features of iris textures and generalizes well to unseen data. The study highlights the potential of compact CNN architectures for reliable and efficient iris-based biometric systems, providing a practical solution for automated eye classification and authentication applications. Future work could focus on expanding the dataset and incorporating additional pre-processing or augmentation techniques to further enhance accuracy and robustness.

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