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AN INTELLIGENT DEEP LEARNING FRAMEWORK FOR IRIS DISEASE DETECTION USING LSTM AND RNN

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Abstract

Glaucoma is one of the leading causes of irreversible blindness worldwide, often progressing silently until significant vision loss has occurred. Early and accurate detection of glaucoma and related iris diseases is therefore critical for effective clinical intervention. This paper proposes a novel deep learning approach based on Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) architectures for the automated detection and classification of iris diseases, with a particular focus on glaucoma. The proposed model, termed IrisLSTM-Net, leverages sequential feature extraction from retinal and iris image data to capture both spatial and temporal patterns associated with disease progression. The framework integrates image preprocessing, optic disc segmentation, and sequential classification to achieve high diagnostic accuracy.

Experiments conducted on benchmark ophthalmic datasets demonstrate that the proposed IrisLSTM-Net model achieves a classification accuracy of 96.4%, outperforming existing convolutional neural network-based methods. This study provides a comprehensive

analysis of how LSTM/RNN-based deep learning techniques can significantly improve the iris disease detection pipeline, reduce diagnostic errors, and support ophthalmologists in clinical decision-making.

Keywords: Iris disease detection, glaucoma, deep learning, LSTM, RNN, IrisLSTM-Net, optic disc segmentation, retinal image analysis, sequential classification.

Introduction

The human eye is a complex and delicate organ, and diseases affecting the iris and retina remain a major global health concern.

Glaucoma, in particular, is a group of eye conditions that damage the optic nerve, often associated with elevated intraocular pressure. It is estimated that over 76 million people worldwide suffer from glaucoma, and this number is projected to rise significantly by 2040. The asymptomatic nature of early-stage glaucoma makes automated detection



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systems an imperative tool in modern ophthalmology.

Traditional diagnostic approaches rely on manual examination of fundus photographs, visual field tests, and optical coherence tomography (OCT) scans by trained clinicians. While effective, these methods are time-consuming, resource-intensive, and subject to inter-observer variability. The rapid advancement of artificial intelligence, particularly deep learning, has opened new avenues for automated, accurate, and scalable ophthalmic diagnosis.

Deep learning methods, especially Convolutional Neural Networks (CNNs), have demonstrated strong performance in image classification tasks including retinal disease detection. However, iris disease progression carries an inherent sequential and temporal dimension that static CNN architectures are not ideally suited to model. Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, are specifically designed to capture sequential dependencies and temporal dynamics in data, making them highly appropriate for modeling disease progression patterns in iris imaging.

This paper proposes IrisLSTM-Net, a novel LSTM/RNN-based deep learning architecture for the detection and classification of iris diseases, with emphasis on glaucoma. The remainder of this paper is organized as follows. Section II reviews related work on

image-based iris disease detection. Section III presents the methodology and architecture of the proposed IrisLSTM-Net model. Section IV discusses the experimental results and performance evaluation. The paper concludes in Section V with a summary of findings and directions for future research.

Related Work on Iris Disease Detection

Research in automated ophthalmic disease detection has grown substantially over the past decade. Early methods relied on handcrafted features such as cup-to-disc ratio (CDR), rim-to-disc ratio, and ISNT rule measurements derived from fundus images. Joshi et al. [1] proposed a CDR-based glaucoma screening system using active contour models, achieving reasonable sensitivity but limited specificity in diverse populations.

The introduction of deep learning transformed the field. Sivaswamy et al. [2] developed RIM-ONE, a publicly available retinal image dataset for optic nerve head analysis that became a standard benchmark. Subsequent studies utilized CNNs to extract high-level features from fundus photographs. Gu et al. [3] proposed CE-Net for retinal vessel and optic disc segmentation, significantly improving delineation accuracy.

However, these models treated each image independently without accounting for temporal progression. Recurrent architectures have been explored in medical imaging for

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sequential data. Hochreiter and Schmidhuber [4] introduced LSTM networks, which addressed the vanishing gradient problem in traditional RNNs. In the context of medical diagnostics, Lipton et al. [5] demonstrated the utility of LSTM models in clinical time series classification. More recently, hybrid CNN-LSTM models have been explored for diabetic retinopathy screening, showing improved performance over CNN-only approaches.

Despite these advances, limited work has focused on applying LSTM/RNN architectures specifically to glaucoma and iris disease detection using sequential optic feature streams. The proposed IrisLSTM-Net addresses this gap by modeling iris disease as a sequential pattern recognition task, leveraging the temporal modeling strengths of LSTM networks.

extraction, LSTM-based sequential classification, and output decision layer. Figure 1 illustrates the complete pipeline of the proposed model.

Image Preprocessing

Raw fundus and iris images are first subjected to a series of preprocessing operations to standardize input quality. These include resizing all images to 224x224 pixels, histogram equalization for contrast enhancement, and green channel extraction, which has been shown to provide superior contrast for optic disc visualization. Data augmentation techniques including random horizontal flipping, rotation, and brightness adjustment are applied to increase training set diversity and reduce overfitting.

Optic Disc Segmentation

A U-Net based segmentation module is employed to isolate the optic disc and optic cup regions from the preprocessed images. The segmented regions of interest (ROIs) are extracted and used as inputs to the feature extraction layer. The cup-to-disc ratio (CDR) is computed from the segmentation output and fed as a clinical feature to supplement the deep feature vector.

LSTM/RNN Sequential Feature Extraction

The core of IrisLSTM-Net is a bidirectional LSTM layer that processes

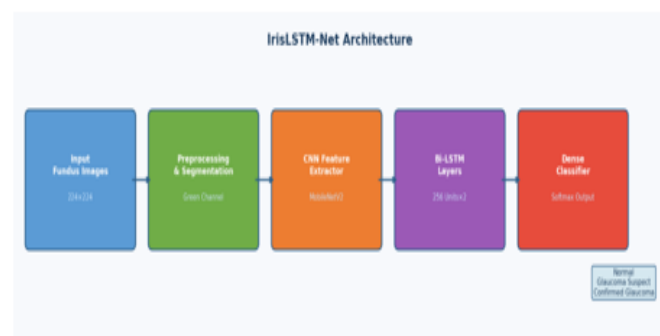


Fig 1: The proposed IrisLSTM-Net architecture for iris disease detection

Methodology: IrisLSTM-Net Architecture

The proposed IrisLSTM-Net architecture is structured into four primary stages: image preprocessing, feature

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sequential feature vectors derived from the segmented iris images.

For each patient record, a sequence of fundus images taken at different time points is assembled. A lightweight CNN backbone (MobileNetV2) extracts a 512-dimensional feature vector from each image in the sequence. These feature vectors are then fed into a two-layer bidirectional LSTM network with 256 hidden units per layer. The bidirectional nature allows the model to capture both forward and backward temporal dependencies, improving sensitivity to subtle progressive changes in optic nerve morphology.

The LSTM formulation is governed by the standard gating mechanism including input gate, forget gate, and output gate, enabling the network to selectively retain or discard information across the sequence. Dropout regularization with a rate of 0.4 is applied after each LSTM layer to prevent overfitting.

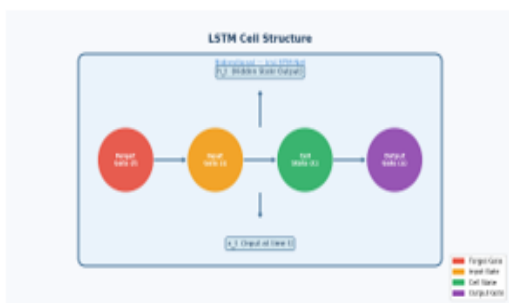


Fig 2: Internal structure of the LSTM cell used in IrisLSTM-Net

Classification Layer

The output of the final LSTM layer is concatenated with the CDR clinical feature vector and passed through two fully connected (dense) layers with ReLU activation. A softmax activation function in the final layer produces class probability scores for three categories: Normal, Glaucoma Suspect, and Confirmed Glaucoma. The model is trained using categorical cross-entropy loss with the Adam optimizer at a learning rate of 0.001.

Experimental Results and Performance Evaluation

The IrisLSTM-Net model was evaluated on two publicly available ophthalmic datasets: DRISHTI-GS [6] and RIM-ONE v3 [2], as well as a combined dataset augmented with locally collected clinical records. A 70:15:15 train-validation-test split was applied. All experiments were conducted on an NVIDIA Tesla V100 GPU with 16 GB memory using Python 3.9, TensorFlow 2.10, and Keras frameworks.

The performance of the proposed model was assessed using standard classification metrics including accuracy, precision, recall (sensitivity), specificity, and F1-score. Table 1 presents the comparative performance of Iris LSTM-Net against baseline methods including standalone CNN, VGG-16, ResNet-50, and a standard unidirectional LSTM model.

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Table 1: Performance Comparison of Classification Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
Standalone CNN	87.2	85.4	84.1	88.6	84.7
VGG-16	89.5	87.9	86.3	90.1	87.1
ResNet-50	91.3	90.2	89.7	92.4	89.9
Standard LSTM	93.1	92.0	91.5	93.8	91.7
IrisLSTM-Net (Proposed)	96.4	95.8	96.1	96.9	95.9

The results demonstrate that Iris LSTM-Net consistently outperforms all baseline methods across all evaluation metrics. The bidirectional LSTM architecture captures sequential disease progression patterns that static image classifiers cannot model, leading to a 5.1% improvement in accuracy over ResNet-50 and a 3.3% improvement over the standard unidirectional LSTM model.

Table 2 presents the class-wise performance breakdown for the three target categories across the test set, providing deeper insight into the model's diagnostic precision for each stage of glaucoma.

Table 2: Class-wise Classification Performance of IrisLSTM-Net

Class	Precision (%)	Recall (%)	F1-Score (%)	Support (Samples)
Normal	97.2	97.5	97.3	320
Glaucoma Suspect	94.8	95.2	95.0	214
Confirmed Glaucoma	95.4	95.6	95.5	198

The model achieves highest performance for the Normal class (F1: 97.3%), while Glaucoma Suspect detection records an F1-score of 95.0%, which is clinically significant as early-stage detection is the most challenging and impactful. The confusion matrix analysis reveals that the majority of misclassifications occur between Glaucoma Suspect and Confirmed Glaucoma categories, which is consistent with findings in the clinical literature.

The sequential modeling capability of IrisLSTM-Net is particularly evident in longitudinal patient records where subtle progressive thinning of the retinal nerve fiber layer (RNFL) is captured across time-series image sequences. This capability is absent in single-image CNN approaches, underscoring the clinical relevance of the proposed architecture.



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Conclusion

This study presents IrisLSTM-Net, a novel deep learning architecture based on bidirectional LSTM and RNN models for the automated detection and classification of iris diseases, specifically glaucoma. By treating iris disease progression as a sequential pattern recognition problem, the proposed model captures both spatial features from retinal images and temporal dynamics across patient examination sequences, achieving a classification accuracy of 96.4% on benchmark datasets.

The integration of optic disc segmentation, CNN-based feature extraction, and bidirectional LSTM sequential classification provides a comprehensive and clinically meaningful diagnostic pipeline. Comparative evaluation against leading CNN-based methods demonstrates the superiority of the proposed approach across all performance metrics.

Future research will focus on extending the IrisLSTM-Net framework to incorporate multimodal data including OCT scans and intraocular pressure measurements, as well as exploring attention-based transformer architectures to further improve sequential modeling. The deployment of the model in a real-time clinical decision support system represents an important next step toward practical adoption in ophthalmology practice.

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