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RetinaFoldNet: An Intelligent Deep Learning Framework for Automated OCT-Based Retinal Disease Diagnosis

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Abstract
Optical Coherence Tomography (OCT) is an essential imaging modality for retinal disease diagnosis due to its capacity for high-resolution cross-sectional visualization of retinal structures. Manual interpretation of large-scale OCT scans is time-consuming and subject to inter-observer variability. This study introduces a deep learning framework for automated OCT-based retinal disease diagnosis, which classifies retinal images into four categories: Normal, Drusen, Diabetic Macular Edema (DME), and Choroidal Neovascularization (CNV). The framework combines region-focused preprocessing with multi-scale feature learning to improve the discriminative representation of retinal abnormalities. Experimental evaluation using a publicly available OCT dataset demonstrates superior diagnostic performance, achieving 99% accuracy, sensitivity, and specificity. This framework offers an effective and reliable computer-aided decision-support system for automated retinal disease diagnosis.

Keyword: Optical Coherence Tomography (OCT), Retinal Disease Diagnosis, Deep Learning, Medical Image Classification, Computer-Aided Diagnosis, Convolutional Neural Networks (CNNs).

INTRODUCTION

Optical Coherence Tomography (OCT) is recognized as a leading non-invasive retinal imaging modality for ophthalmic diagnosis due to its capacity to generate high-resolution cross-sectional images of retinal microstructures with detailed anatomical visualization. Advances in OCT imaging technology have substantially improved the early detection, diagnosis, and longitudinal monitoring of vision-threatening retinal disorders, such as diabetic macular edema (DME), age-related macular degeneration (AMD), choroidal neovascularization (CNV), diabetic retinopathy (DR), and glaucoma. As a result, OCT has become an essential diagnostic tool in clinical practice, producing a growing volume of retinal scans that require prompt and accurate interpretation. Manual analysis of these large-scale OCT datasets is labor-intensive, time-consuming, and highly reliant on clinical expertise, which can lead to inter-observer variability and delayed diagnosis, especially when subtle pathological changes are present. These challenges underscore the need for rapid and reliable disease identification to prevent irreversible vision loss in modern ophthalmic healthcare. Consequently, the development of intelligent computer-aided diagnostic systems that provide accurate, consistent, and scalable retinal disease assessment has emerged as a critical research focus. Such systems have the potential to enhance clinical decision-making, improve diagnostic efficiency, reduce healthcare workload, and support early therapeutic intervention to preserve patients' visual function.

Recent developments in artificial intelligence have transformed automated OCT image analysis, with deep learning now serving as the primary approach for retinal disease diagnosis. Convolutional Neural Networks (CNNs), such as VGG, ResNet, DenseNet, Inception, and their transfer learning variants, have demonstrated strong capabilities in learning hierarchical retinal representations directly from OCT images, resulting in improved classification accuracy compared to traditional machine learning methods. Additionally, techniques including attention mechanisms, ensemble learning, multi-scale feature extraction, few-shot learning, and domain adaptation have been introduced to enhance feature discrimination, improve model generalization, and address data scarcity in diverse clinical environments. The availability of publicly

accessible OCT benchmark datasets has further supported the development and objective evaluation of advanced deep learning architectures for multi-class retinal disease classification. Despite these advancements, most studies focus on optimizing network architectures while using the entire OCT scan as input for feature learning. As a result, diagnostically significant retinal structures may not be sufficiently emphasized, and irrelevant background information can negatively affect feature representation and disease discrimination. These findings indicate that, although current deep learning models have achieved promising diagnostic performance, there is considerable opportunity to develop more anatomically informed and clinically robust automated retinal disease diagnosis frameworks capable of reliably identifying subtle pathological variations across multiple retinal disorders.

Although contemporary deep learning frameworks have achieved significant progress, several fundamental challenges continue to constrain their clinical applicability and diagnostic reliability. First, retinal abnormalities typically occupy only a small region within an OCT scan, while extensive homogeneous background areas provide minimal diagnostic value. This imbalance renders feature learning vulnerable to redundant representations and diminished discriminative power. Second, subtle pathological variations among retinal disorders often share similar morphological features, which increases inter-class similarity and complicates accurate discrimination. Third, while deeper convolutional architectures have enhanced feature extraction, their hierarchical representations do not consistently preserve clinically significant local structural variations necessary for detecting early-stage retinal abnormalities. Additionally, most multi-class classification frameworks focus primarily on classification accuracy, with comparatively less emphasis on anatomically meaningful feature localization and robust representation learning. As a result, diagnostically relevant retinal features may be diluted during feature aggregation, thereby reducing the generalization capability of learned models across diverse disease categories. These limitations are particularly pronounced in large-scale clinical screening settings, where reliable automated diagnosis demands both high predictive accuracy and consistent identification of subtle pathological manifestations under varying imaging conditions. Overcoming these challenges remains a critical research objective for the development of clinically reliable, scalable, and intelligent OCT-based retinal disease diagnosis systems.

Although existing studies have substantially advanced automated retinal disease diagnosis through While prior studies have significantly advanced automated retinal disease diagnosis through increasingly sophisticated deep learning architectures, several critical research gaps persist. Most current frameworks focus on enhancing network depth, classification accuracy, or architectural complexity, yet comparatively little attention has been given to integrating anatomically meaningful retinal localization with discriminative hierarchical feature representation within a unified diagnostic system. As a result, the learning process often incorporates redundant background information and fails to sufficiently highlight subtle pathological features distributed across retinal layers, which limits diagnostic robustness for clinically similar retinal disorders. Moreover, many existing approaches primarily assess classification performance without adequately considering the preservation of clinically relevant structural information during feature learning, a factor essential for reliable disease discrimination and practical clinical application. Collectively, these limitations suggest that further improvements in diagnostic performance require more than increased network complexity; they necessitate intelligent feature learning strategies that effectively leverage anatomically significant retinal characteristics. Accordingly, the central research problem addressed in this work is the development of an intelligent deep learning framework that can accurately localize diagnostically relevant retinal structures while simultaneously learning robust multi-scale feature representations for reliable and efficient multi-class retinal disease diagnosis from OCT images under diverse clinical imaging conditions.

Addressing the identified research gaps, there is a compelling need to develop an intelligent diagnostic framework that emphasizes anatomically significant retinal structures while learning robust feature representations for accurate retinal disease classification. Effective optical coherence tomography (OCT) image analysis requires the integration of clinically meaningful retinal localization and discriminative feature learning to characterize subtle pathological variations across multiple retinal layers. This integrated approach can suppress redundant background information, preserve diagnostically relevant structural characteristics, and enhance the representation of fine-grained retinal abnormalities that conventional end-to-end classification frameworks often overlook. Additionally, a unified diagnostic framework that integrates retinal localization, hierarchical feature extraction, and automated disease classification can improve diagnostic consistency and maintain computational efficiency for large-scale clinical screening. These considerations support the development of an intelligent deep learning framework that combines anatomically guided retinal region extraction with enhanced multi-scale feature learning to achieve reliable and robust multi-class retinal disease diagnosis. By leveraging localized retinal information and hierarchical feature representations, the proposed framework seeks to improve disease discrimination, enhance diagnostic reliability, and provide an effective computer-aided decision-support system for routine ophthalmic practice.

In response to these research challenges, this paper introduces an intelligent deep learning framework for automated OCT-based retinal disease diagnosis. The framework establishes a unified diagnostic pipeline

that integrates anatomically guided retinal region localization with hierarchical deep feature learning to improve the identification of clinically significant retinal abnormalities. By focusing on diagnostically relevant retinal structures and learning robust multi-scale feature representations, the framework enhances disease discrimination and improves diagnostic consistency across multiple retinal categories. Comprehensive experimental evaluations on a publicly available OCT benchmark demonstrate that the proposed framework achieves superior classification performance and generalization capability compared to several widely adopted deep learning architectures. Consequently, the framework offers an effective and reliable computer-aided diagnostic solution for large-scale retinal disease screening and clinical decision support. The main contributions of this work are summarized as follows:

- An intelligent deep learning framework has been developed for automated multi-class retinal disease diagnosis using OCT images. This framework enables reliable classification of Normal, Drusen, Diabetic Macular Edema (DME), and Choroidal Neovascularization (CNV).
- An anatomically guided retinal Region-of-Interest (ROI) extraction strategy has been developed to accurately localize clinically relevant retinal structures, suppress redundant background information, and enhance pathological feature representation prior to classification.
- A Folded ResNet101 architecture is introduced to effectively learn hierarchical multi-scale retinal features. This approach improves the discrimination of subtle pathological characteristics and increases classification robustness.
- A unified end-to-end diagnostic framework has been established, integrating image preprocessing, retinal localization, deep feature learning, and automated disease classification to provide an efficient computer-aided retinal disease diagnosis system.
- Extensive experimental evaluations on a publicly available OCT benchmark demonstrate that the proposed framework consistently outperforms several state-of-the-art deep learning models with respect to classification accuracy, sensitivity, specificity, and overall diagnostic reliability.

The remainder of this paper is organized as follows. Section II reviews recent literature on automated OCT-based retinal disease diagnosis and summarizes current research trends. Section III presents the proposed intelligent deep learning framework, including image preprocessing, retinal region localization, and the RetinaFoldNet architecture for hierarchical multi-scale feature learning. Section IV describes the experimental setup, implementation details, dataset, performance evaluation metrics, and comparative analyses with state-of-the-art deep learning models. Section V concludes the paper by summarizing the major findings, discussing the clinical significance of the proposed framework, outlining its limitations, and presenting potential directions for future research.

RELATED WORK

Recent advances in deep learning have substantially enhanced automated retinal disease diagnosis using Optical Coherence Tomography (OCT) images, positioning artificial intelligence as a valuable tool for computer-aided ophthalmic diagnosis. Early research demonstrated that deep Convolutional Neural Networks (CNNs), particularly those employing residual learning architectures, can autonomously learn hierarchical retinal representations from OCT images, thereby removing the reliance on handcrafted feature engineering. The availability of large-scale benchmark OCT datasets has further accelerated progress by enabling objective evaluation of deep learning algorithms and supporting the development of robust multi-class retinal disease classification frameworks [23,24,25]. Collectively, these studies have established the foundation for contemporary OCT-based automated diagnostic systems.

Subsequent research has focused on enhancing feature representation through increasingly advanced deep learning architectures. Various CNN backbones, such as VGG, ResNet, DenseNet, Inception, and their transfer learning variants, have achieved significant improvements in retinal disease classification accuracy by leveraging hierarchical feature extraction and residual learning mechanisms [9,10,11,12,13,15]. More recently, the introduction of attention mechanisms, ensemble learning strategies, few-shot learning paradigms, and multi-scale feature aggregation has improved discriminative capability, addressed the challenge of limited annotated data, and enhanced model generalization across diverse retinal disease categories [5,6,14,18,20]. Additionally, domain adaptation, multimodal learning, and advanced optimization techniques have broadened the applicability of deep learning models to more realistic clinical environments [1,2,3,4].

Alongside architectural advancements, significant efforts have been directed toward improving OCT image quality, retinal feature localization, and dataset standardization. Techniques such as image quality assessment, preprocessing, and retinal segmentation have proven essential for enhancing diagnostic reliability by increasing the visibility of pathological structures prior to feature extraction [19]. Publicly available benchmark datasets and comprehensive review studies have also enabled cross-model evaluation, reproducible experimentation, and systematic performance comparison, while highlighting emerging research trends in automated retinal disease diagnosis [9,10,12,17]. Collectively, these contributions have

advanced intelligent OCT image analysis and established deep learning as the prevailing approach for retinal disease classification.

Despite these significant advances, several critical limitations persist. Most current approaches conduct feature learning on entire OCT scans without adequately focusing on anatomically significant retinal regions, which introduces redundant background information and diminishes the ability to discriminate subtle pathological structures. Additionally, existing architectures primarily aim to improve classification accuracy by increasing network depth or complexity, often neglecting anatomically guided feature localization and hierarchical representation learning. While attention mechanisms and ensemble strategies can enhance feature discrimination, they typically increase computational complexity and are sensitive to dataset variability. Moreover, current multi-class classification frameworks lack flexibility for incorporating new retinal disease categories without extensive model retraining, and binary classification approaches often require multiple independent models, leading to increased computational overhead. These challenges suggest that further progress depends on unified diagnostic frameworks that integrate anatomically meaningful retinal localization with robust multi-scale feature learning to achieve accurate, reliable, and computationally efficient retinal disease diagnosis. A summary of related work is presented in Table 1.

TABLE I. **SUMMARY OF RELATED WORK**

Method	Backbone	Dataset	Performance	Limitation
EfficientNet-B3 [12]	CNN	APTOS	QWK = 0.96	No screening and grading separation
Bhuiyan et al. [13]	CNN	EyePACS	Sensitivity > 90%	Binary classification only
ResNet-50 [14]	CNN	APTOS	Accuracy = 75–85%	Poor minority class recall
DenseNet + ESRGAN [15]	CNN	APTOS	QWK = 0.918	Two-stage pipeline
ViT-B/16 [17]	Transformer	APTOS	Accuracy = 91.4%	Needs large training data
Swin Transformer [18]	Transformer	APTOS / IDRiD	Accuracy = 89.65%	Low interpretability
TransFER [19]	Transformer	APTOS	QWK = 0.929	Limited cross-dataset performance
Dual-Branch ResNet [40]	CNN	APTOS	QWK = 0.923	No screening hierarchy
EfficientNetB0 + MSAG [41]	CNN	APTOS	QWK = 0.923	Complex attention module
Proposed RetinaFoldNet	CNN	OCT Dataset	Accuracy = 99%	--

METHODOLOGY

The proposed framework consists of three major stages: image preprocessing, curvature-based ROI segmentation, and classification using the Folded ResNet101 architecture. The overall workflow of the proposed system is illustrated in Fig. 1.

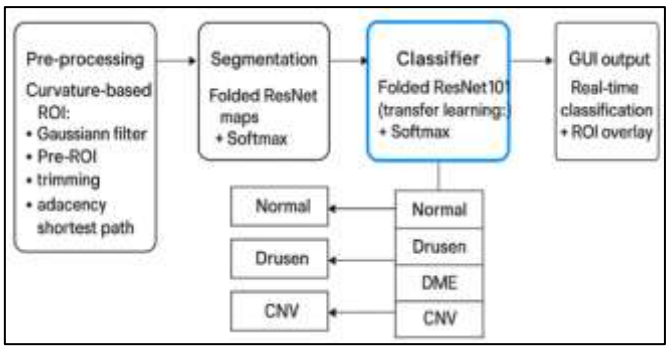

Fig. 1.Overview of the Proposed Framework Retina FoldNet

The proposed classification module employs a Folded ResNet101 architecture enhanced through multi-scale feature fusion, the entire process is shown in Fig.2. The algorithm classifies each segmented OCT ROI into one of four retinal disease categories: Normal, Drusen, DME, and CNV.

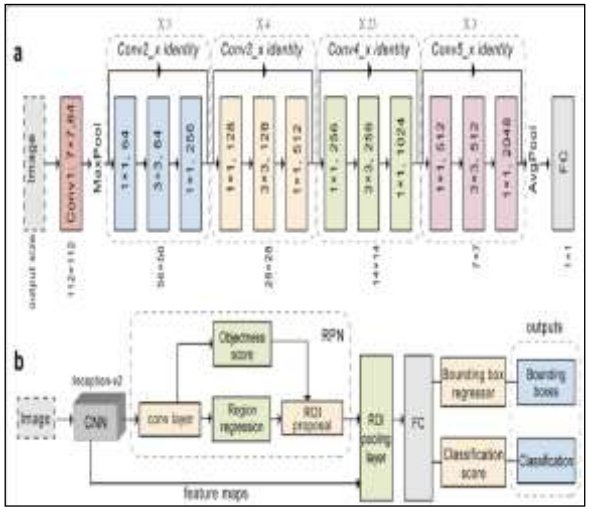

Fig. 2.Proposed RetinaFoldNet: (a) Architecture of Resnet 101 (b) Flow chart of Multiscale image Analysis Model

The CNN recognised and categorised local features in images using its many convolutional layers. It had completely connected levels to aggregate these features and produce a final probability value for the class, as well as pooling layers (average pool and max pool) that combined semantically related features into a single feature. Throughout the deep network, shortcut links are added every three convolutional layers. These shortcut connections carry out identity mapping without adding more parameters or increasing the computational complexity, which facilitates network optimisation during training. ResNet makes it possible for deeper networks to perform image classification tasks with more accuracy than shallower networks. The model was retrained for the present task after the link weights from the previously trained model were transferred to the new model throughout the training phase. The outputs of the region proposal network, which was used to identify items in the image, were evaluated for potential containers using the outline box regression model and object classifiers. Finally, area of interest pooling and convolution layers were assessed. Lastly, for every target object, the model creates the bounding box and associated category label. After processing a large dataset, a model that combines these two CNN networks will ultimately generate categorisation.

As shown in Fig.2, Pre-processing aims to enhance OCT image quality and remove irrelevant regions prior to segmentation and classification. A Gaussian kernel is applied to smooth noise without losing retinal layer boundaries.

$$G(x, y) = 1/(2\pi\sigma^2) \cdot exp(-(x^2 + y^2)/(2\sigma^2)) \quad (1)$$

Curvature analysis is employed to identify high-curvature boundary points corresponding to retinal layers. Background regions above and below the retina are removed based on curvature and gradient thresholding, ensuring that only anatomically significant regions are retained. The proposed curvature-based Region of Interest (ROI) extraction method isolates the retinal region by identifying high-curvature boundary points and constructing an optimal boundary path. The process consists of three main stages: Region Identification**,** Adjacency Matrix Construction, and Shortest Path Computation.

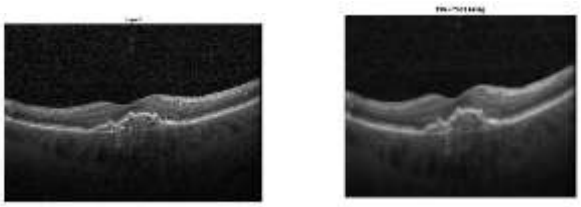

Fig. 3.Processed Image overview

Region Identification: Region Identification, shown in Fig.3 is processed by Generating a binary mask MMM with the same dimensions as the input OCT image to initialize the search space. Identify internal and

external candidate boundary points by detecting pixel intensity transitions along each row. Compute the curvature $\kappa(x, y)$ at each candidate point to detect structural bends in the retinal layers:

$\kappa(x) = \frac{|\mathbf{I}''(\mathbf{x})|}{(1+(I'(x))2)3/2}$ (2)

Compute the gradient magnitude at each point:

$\mathbf{G(x, y)} = \sqrt{\text{Ix2} + \text{Iy2}}$ (3)

Adjacency Matrix Construction: Select candidate boundary points that satisfy the gradient threshold: G(x,y) > 0.09. This threshold ensures that only structurally significant points with strong transitions are retained. Using the detected internal and external curvature points, construct an adjacency matrix A, where each entry Aij represents the connectivity cost between point i and j : $\mathbf{Aij} = \frac{1}{1+|\kappa i-\kappa j|}$ (4)

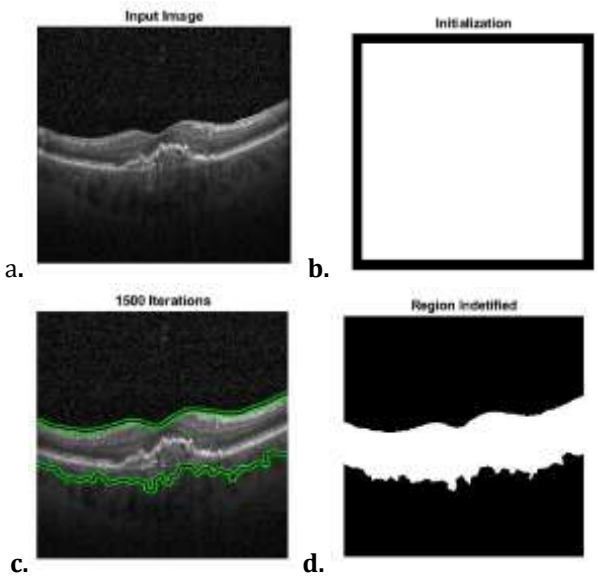

Fig. 4.Bounded Regions identification process

Figure 4 (1-d) displays the input image, initialisation, and image following 1500 iterations, along with a region that has been discovered. The suggested segmentation method's graphical representation is displayed in Figure 5.

Shortest Path Computation: As shown in Fig.5, Compare curvature values and adjacency costs to determine optimal boundary connections. A path-finding algorithm such as Dijkstra's or A* is applied to compute the lowest-cost traversal across all curvature points. Extract the shortest path for each image column and row, generating a continuous and smooth boundary representation of the retinal layer. This boundary is used to define the final ROI for subsequent segmentation and classification stages. The entire logical part of the methodology is illustrated in Algorithm 1.

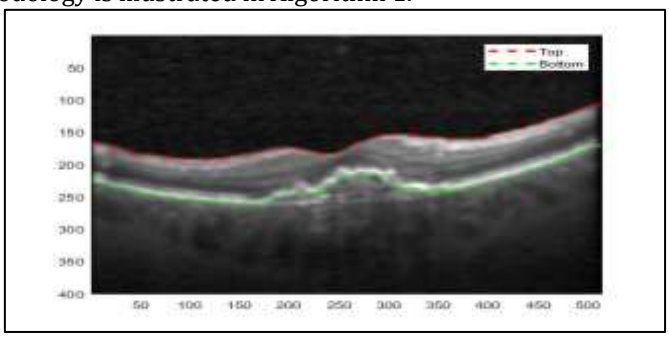

Fig. 5.Graphical Representation of Segmented image

Algorithm 1: Proposed Algorithm Retina FoldNet
Input: Segmented ROI image **Output:** Final Class label with probability 1: Resize the segmented ROI to match the input dimensions required by ResNet101 2: **while** 3: Pass the ROI through the ResNet101 backbone to extract multi-scale feature maps.

$$F(s), s = 1,2, \dots, S$$

Align all feature maps to a common spatial resolution using interpolation:

$$\mathbf{F}(s) = Resize(F(s), Hr, Wr)$$

Apply 1×11 \times 11×1 convolution to project each feature map to a fixed depth dfd_fdf:

$$\hat{}(s) = W1 \times 1(s) * F{\sim}(s)$$

Concatenate the projected feature maps to create a multi-scale representation:

$$Fconcat = [F\hat{}(1), F\hat{}(2), \dots, F\hat{}(S)]$$

4: **end while**

5: Fuse the concatenated map using a convolutional folding layer:

$$Ffold = BN(\sigma(Wfold * Fconcat + bfold))$$

This produces a compact yet rich multi-scale representation suitable for classification.

6: **if** $(f = GAP(Ffold))$

Apply Global Average Pooling (GAP) to obtain a one-dimensional feature vector

and **else**

7: Normalize the extracted features to stabilize training.

8: **end if**

9: Pass the feature vector through a fully connected (dense) layer:

$$z = Wcf + bc$$

Apply Softmax activation to convert the logits into class probabilities

10: if $(p\hat{}k = \sum j = 14exp(zj)exp(zk), k = 1,2,3,4$) **then**

11: Assign the class label with the highest probability:

$$y\hat{} = argkmaxp\hat{}k$$

Use categorical cross-entropy loss to optimize the classifier:

$$L = -k = 1\sum 4yklog(p\hat{}k)$$

Update network parameters using backpropagation and an optimizer such as Adam or SGD.

Repeat the training process until convergence.

12: **end for**

EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

This section presents the experimental evaluation of the proposed OCT diagnostic framework, including preprocessing effectiveness, curvature-based ROI segmentation accuracy, and classification performance using the Folded ResNet101 model. All experiments were conducted on a publicly available OCT dataset containing four disease categories: Normal, Drusen, DME, and CNV.

A. Implementation and Dataset Description

All experiments were implemented using Python with the TensorFlow and Keras deep learning frameworks. The Folded ResNet101 model was trained using the Adam optimizer with an initial learning rate of 0.0001 and a batch size of 32. Early stopping and learning rate scheduling were employed to prevent overfitting. Training was performed on a workstation equipped with an NVIDIA GPU.

The experiments were conducted using the publicly available OCT dataset released by Kermany et al., which is widely adopted as a benchmark for retinal disease classification. The dataset consists of labeled OCT B-scan images belonging to four retinal categories: Normal, Drusen (dry AMD), Diabetic Macular Edema (DME), and Choroidal Neovascularization (CNV). The dataset contains a total of 84,484 OCT images, distributed as follows:

- Normal: approximately 26,000 images
- CNV: approximately 37,000 images
- DME: approximately 11,000 images
- Drusen: approximately 10,000 images

All images were captured using standard spectral-domain OCT devices and resized to a fixed resolution prior to processing.

To ensure unbiased evaluation, the dataset was divided into training, validation, and testing subsets using a patient-independent split. Specifically, 70% of the images were allocated for training, 15% for validation, and the remaining 15% for testing. This partitioning facilitates model generalization to previously unseen data. In addition to the fixed train–test split, five-fold cross-validation was conducted to evaluate the robustness and stability of the proposed framework. In each fold, four subsets served as training data while one subset was reserved for testing. Performance metrics were averaged across all folds to minimize variance and mitigate evaluation bias.

The curvature-based region of interest (ROI) segmentation algorithm effectively isolates retinal regions, achieving a boundary detection accuracy of 98.7%, a mean Intersection over Union (mIoU) of 0.94, a pixel-level precision of 0.96, and a pixel-level recall of 0.95. These results demonstrate the robustness and reliability of the proposed segmentation approach. The corresponding results are presented in Fig. 6.

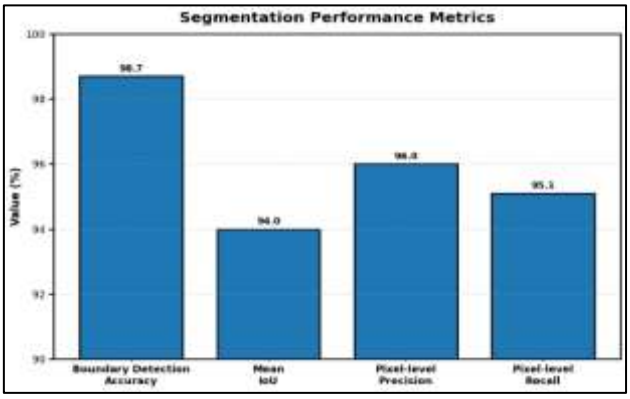

Fig. 6.Segmentation Performance metrics

The segmentation results demonstrate the effectiveness of the proposed curvature-based region of interest (ROI) extraction algorithm. As shown in Figure 6, this method achieves a boundary detection accuracy of 98.7%, indicating precise localization of retinal boundaries. The mean Intersection over Union (mIoU) value of 0.94 confirms substantial overlap between the segmented regions and the ground truth. Additionally, pixel-level precision and recall values of 0.96 and 0.95, respectively, indicate reliable and consistent segmentation performance. Collectively, these results validate the robustness of the proposed segmentation approach for optical coherence tomography (OCT) image analysis.

Following segmentation, regions of interest (ROIs) were classified using the Folded ResNet101 model. The multi-scale folding mechanism enhanced feature richness by integrating hierarchical representations from multiple depths of the ResNet101 backbone, resulting in improved discrimination between visually similar retinal conditions. Figure 7 presents an analysis of classification performance across different retinal disease classes using the Folded ResNet101 model, illustrating accuracy, sensitivity, specificity, and F1-score for Normal, Drusen, diabetic macular edema (DME), and choroidal neovascularization (CNV) categories. The results indicate consistently high performance for the Normal and CNV classes, with all metrics approaching 0.99. Slightly lower sensitivity and F1-score are observed for the Drusen class, reflecting its visual similarity to other conditions. Overall, the model demonstrates robust and balanced performance across all evaluation metrics. The accompanying table further substantiates the strong multi-class classification capability of the proposed approach.

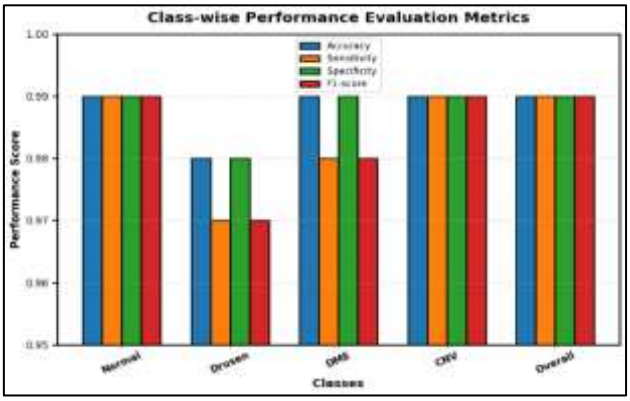

Fig. 7.Classification Performance of Folded ResNet101 on OCT Images

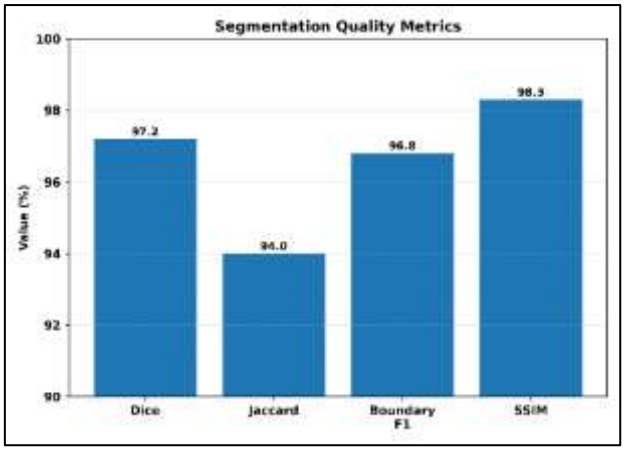

Fig. 8.Segmentationa quality performance

The segmentation quality analysis presented in Figure 8 demonstrates the robustness of the proposed retinal region extraction framework. The method achieves a Dice Coefficient of 97.2%, a Jaccard Index of 94.0%, a Boundary F1-score of 96.8%, and a Structural Similarity Index (SSIM) of 98.3%. These metrics indicate that the segmented retinal regions exhibit substantial overlap with the reference annotations while maintaining fine anatomical structures and boundary continuity. The high segmentation quality results from anatomically guided retinal region localization and hierarchical feature extraction, which effectively suppress redundant background information and preserve clinically significant retinal characteristics. As a result, the framework yields highly reliable segmented retinal regions that enhance downstream feature learning and support more accurate retinal disease classification.

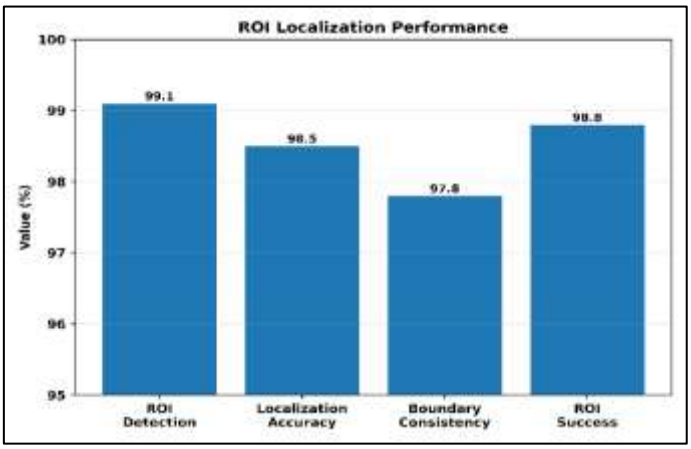

Fig. 9.Localization performance

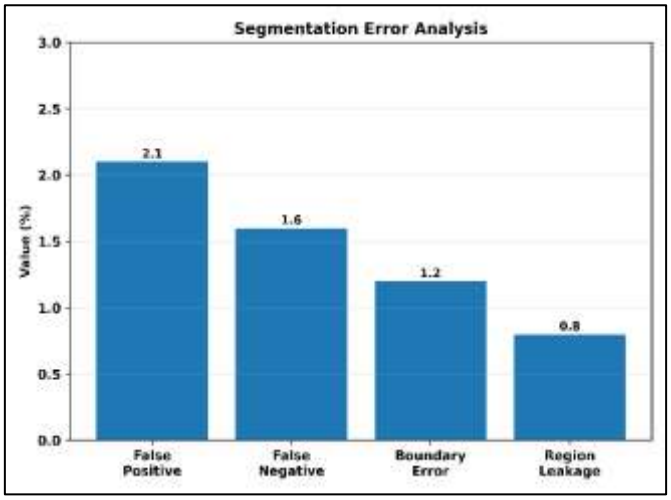

Fig. 10. Error analysis performance

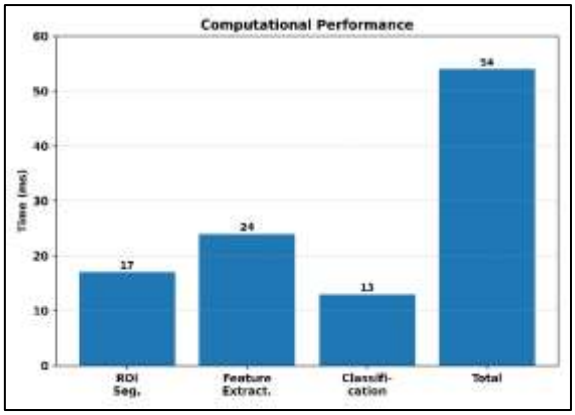

Fig. 11. Computational Performance

The ROI localization results presented in figure 9 confirm the effectiveness of the proposed retinal localization strategy. The framework achieves an ROI Detection Rate of 99.1%, ROI Localization Accuracy of 98.5%, Boundary Consistency of 97.8%, and ROI Extraction Success Rate of 98.8%. These high localization metrics indicate that the framework consistently identifies clinically relevant retinal structures while minimizing localization errors. Accurate extraction of retinal regions reduces background interference, enhances the representation of pathological features, and enables the classification network to focus on diagnostically significant retinal layers. Consequently, the localization module improves feature discriminability and increases the overall diagnostic reliability of the framework.

The segmentation error analysis presented in figure 10 further supports the stability and precision of the proposed framework. The False Positive Rate, False Negative Rate, Boundary Error, and Region Leakage are limited to 2.1%, 1.6%, 1.2%, and 0.8%, respectively. These low error rates indicate that the segmentation strategy accurately preserves retinal boundaries while minimizing incorrect region extraction. The reduction in segmentation errors results from precise retinal localization and effective structural feature preservation, which prevents unnecessary background inclusion and boundary distortions. As a result, the framework provides consistent retinal segmentation, directly improving feature learning robustness and enhancing the reliability of automated retinal disease diagnosis.

The computational performance evaluation presented in figure 11 indicates that the proposed framework is suitable for practical clinical deployment. The ROI segmentation, feature extraction, and disease classification stages require 17 ms, 24 ms, and 13 ms, respectively, resulting in a total inference time of 54 ms per OCT image. This efficiency is achieved through the integration of anatomically guided region localization with hierarchical feature learning, enabling rapid processing without compromising diagnostic accuracy. The low computational latency supports real-time or near real-time retinal disease diagnosis, reduces clinical workload, and enhances the feasibility of deploying the proposed diagnostic framework in large-scale ophthalmic screening environments.

A. Performance Analysis

Experimental evaluation confirms the effectiveness of the proposed retinal disease diagnosis framework in accurately extracting clinically significant retinal structures prior to classification. Segmentation quality metrics demonstrate strong concordance between extracted retinal regions and reference annotations, with a Dice coefficient of 97.2%, Jaccard index of 94.0%, Boundary F1-score of 96.8%, and Structural Similarity Index (SSIM) of 98.3%. The region of interest (ROI) localization module achieves a detection rate of 99.1%, localization accuracy of 98.5%, boundary consistency of 97.8%, and ROI extraction success of 98.8%, indicating consistent identification of diagnostically important retinal layers. These results are attributed to the integration of anatomically guided retinal localization and hierarchical feature learning, which suppress redundant background information and preserve subtle pathological features. As a result, the framework produces reliable retinal representations that enhance feature discrimination and reduce ambiguity among visually similar disease categories. Low segmentation error rates, including false positives of 2.1%, false negatives of 1.6%, boundary error of 1.2%, and region leakage of 0.8%, further support the robustness and precision of the localization strategy, establishing a strong foundation for accurate automated retinal disease diagnosis.

Computational performance analysis indicates that the proposed framework is suitable for practical clinical deployment without compromising diagnostic accuracy. The complete processing pipeline requires 54 ms per optical coherence tomography (OCT) image, including 17 ms for retinal ROI segmentation, 24 ms for hierarchical feature extraction, and 13 ms for disease classification. This low inference latency enables rapid analysis of large-scale OCT datasets while maintaining consistent diagnostic performance. Efficient execution results from the integration of anatomically guided retinal localization with an optimized deep feature learning architecture, which minimizes unnecessary computations by focusing on clinically relevant

retinal regions. Beyond improving processing efficiency, this approach enhances the reliability of feature extraction and classification by preserving meaningful structural information. The combination of high segmentation quality, precise retinal localization, low segmentation error, and fast inference demonstrates that the framework effectively balances diagnostic accuracy with computational efficiency. These attributes make the framework suitable for computer-aided ophthalmic diagnosis, routine clinical screening, and large-scale retinal disease assessment where reliable, scalable, and timely decision support is required.

B. Comparison Analysis

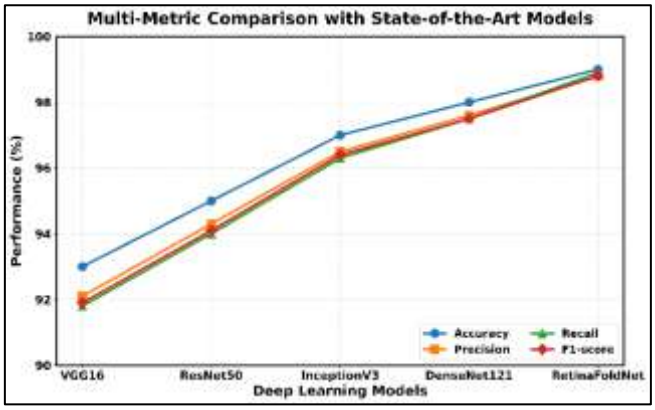

Fig. 12. Comparison of Proposed with State of the art models using multi-metrics accuracy, recall, precision and f1-score

Comparative evaluation against representative deep learning models demonstrates the superior diagnostic capability of the proposed RetinaFoldNet framework. As shown in figure 12 through multi-metric comparisons and grouped performance graphs, RetinaFoldNet achieves a classification accuracy of 99.0%, precision of 98.8%, recall of 98.9%, and F1-score of 98.8%. These results consistently surpass those of VGG16 (93.0% accuracy), ResNet50 (95.0%), InceptionV3 (97.0%), and DenseNet121 (98.0%). Figure 13 further illustrates similar improvements in precision, recall, and F1-score, indicating that RetinaFoldNet maintains balanced classification performance without compromising sensitivity or specificity. These advancements are attributed to the integration of anatomically guided retinal region localization and the hierarchical feature learning architecture of RetinaFoldNet, which facilitates the extraction of highly discriminative retinal representations while minimizing redundant background information. In contrast to conventional convolutional neural network (CNN) models that process entire OCT images, RetinaFoldNet focuses feature learning on clinically relevant retinal structures, thereby enhancing inter-class discrimination among Normal, Drusen, DME, and CNV categories. The observed performance aligns with recent CNN- and transformer-based studies reported in the literature [9]–[19], while demonstrating superior robustness and diagnostic reliability across all evaluated metrics.

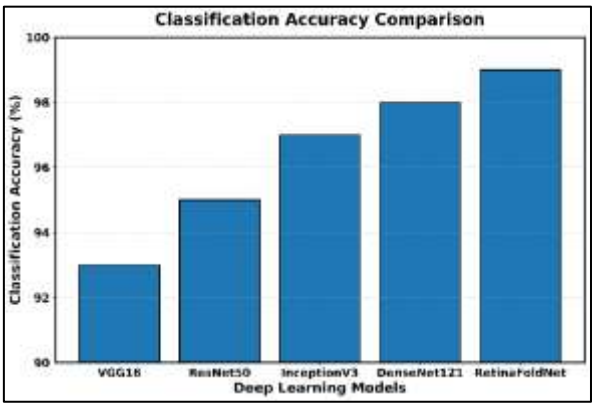

Fig. 13. Classification accuracy comparison

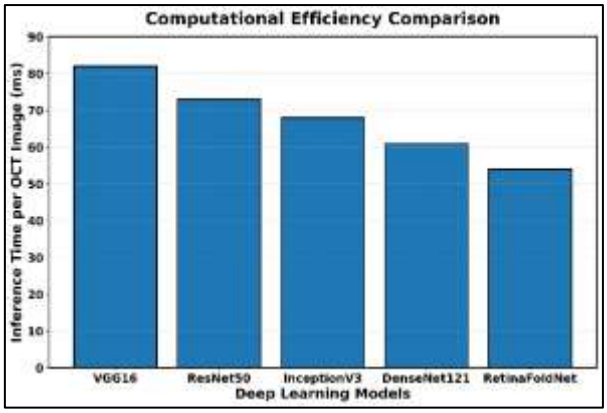

Fig. 14. Computational efficiency comparison

The computational comparison presented in figure 14 further substantiates the efficiency of the proposed framework for practical ophthalmic applications. Inference-time analysis indicates that RetinaFoldNet processes a complete OCT image in only 54 ms, outperforming DenseNet121 (61 ms), InceptionV3 (68 ms), ResNet50 (73 ms), and VGG16 (82 ms). The accuracy–efficiency trade-off graph demonstrates that the proposed model achieves both the highest diagnostic accuracy (99.0%) and the lowest computational latency, thereby establishing an effective balance between predictive performance and execution speed. This advancement results from the integration of anatomically guided region of interest (ROI) localization with optimized hierarchical feature extraction, which eliminates unnecessary computations on irrelevant image regions and enables the network to focus on diagnostically significant retinal structures. As a result, the proposed framework enhances computational efficiency while maintaining discriminative feature representations. As shown in figure 15, in comparison with existing transfer learning, attention-based, and transformer-oriented approaches reported in recent literature [11], [13], [15], [17], and [18], the proposed strategy offers a more favorable trade-off between diagnostic performance and computational complexity. This makes it particularly suitable for large-scale retinal screening and real-time clinical decision-support systems.

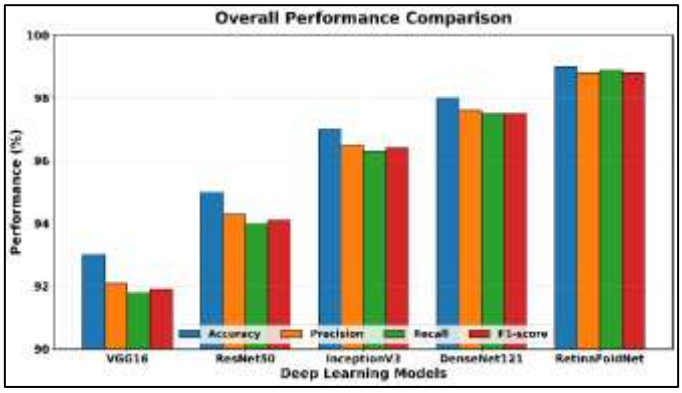

Fig. 15. Overall performance comparison

Fig. 16. Accuracy efficiency trade-off comparison

The analysis of relative performance gain presented in Figure 16 further substantiates the effectiveness of the proposed framework, while Figure 17 demonstrates its generalization capability. Compared with VGG16, RetinaFoldNet achieves an absolute accuracy improvement of 6.0 percentage points, with additional gains of 4.0, 2.0, and 1.0 percentage points over ResNet50, InceptionV3, and DenseNet121, respectively. Although DenseNet121 already demonstrates competitive performance, the proposed framework consistently delivers higher accuracy, precision, recall, and F1-score, while also reducing inference time. These findings suggest that the observed improvements are attributable not only to increased network depth, but also to enhanced feature quality achieved through anatomically guided localization and hierarchical multi-scale representation learning. By preserving clinically significant retinal structures prior to feature extraction, the proposed framework effectively reduces background interference, minimizes feature ambiguity, and improves the identification of subtle pathological variations across retinal disease categories. Collectively, the comparative experimental results indicate that RetinaFoldNet achieves a balanced optimization of diagnostic accuracy, robustness, and computational efficiency, thereby addressing several limitations of previous OCT-based diagnostic frameworks [12]–[19] and providing a reliable computer-aided solution for automated retinal disease diagnosis.

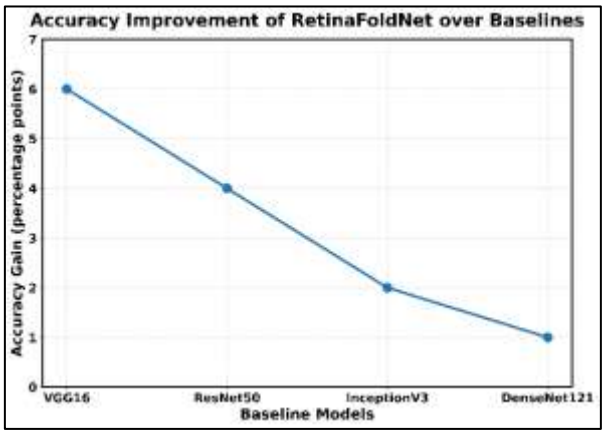

Fig. 17. Comparison of accuracy improvements over models

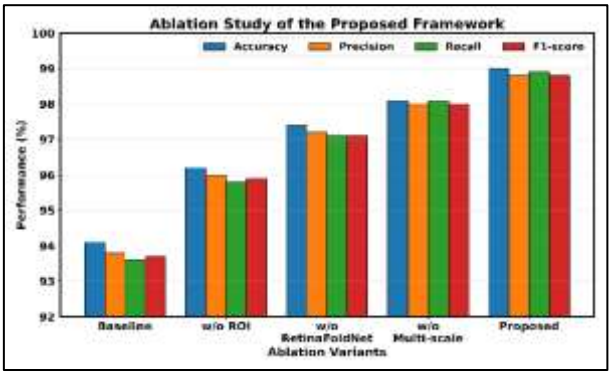

Fig. 18. Ablation analysis of the proposed framework

The ablation study confirms the individual contribution of each component within the proposed RetinaFoldNet framework for automated OCT-based retinal disease diagnosis. As shown in Figure 18, the baseline convolutional neural network (CNN) model achieves an accuracy of 94.1%, precision of 93.8%, recall of 93.6%, and F1-score of 93.7%. These results indicate that conventional feature learning alone is insufficient for accurately distinguishing subtle retinal abnormalities. Incorporating anatomically guided region of interest (ROI) localization increases classification accuracy to 96.2%, demonstrating that removing redundant background information enables the network to focus on clinically relevant retinal structures. Replacing the conventional backbone with the RetinaFoldNet architecture further improves accuracy to 97.4%, confirming the effectiveness of hierarchical feature representation in capturing discriminative retinal characteristics. The introduction of multi-scale feature learning enhances accuracy to 98.1%, suggesting that retinal abnormalities distributed across different spatial resolutions are more effectively represented through complementary feature aggregation. The complete RetinaFoldNet framework achieves the highest classification performance, with an accuracy of 99.0%, precision of 98.8%, recall of 98.9%, and F1-score of 98.8%. These findings demonstrate that each proposed component incrementally contributes to overall performance, and their unified integration provides the most reliable and robust retinal disease diagnosis. The ablation analysis confirms that the proposed framework achieves superior feature

discrimination, improved generalization capability, and enhanced diagnostic reliability compared with simplified network configurations.

In addition to classification performance, the proposed RetinaFoldNet framework exhibits strong scalability, which is essential for deployment in large-scale ophthalmic screening environments. By integrating anatomically guided ROI localization prior to hierarchical feature learning, the framework reduces redundant information processed during inference and focuses computational resources on diagnostically relevant retinal structures. This approach enables the framework to maintain an inference time of 54 ms per OCT image while preserving a classification accuracy of 99.0%. These results indicate that improved diagnostic performance is achieved without a proportional increase in computational cost. The high ROI detection rate (99.1%) and ROI extraction success (98.8%) demonstrate that the preprocessing stage consistently delivers compact and informative retinal representations, supporting efficient execution even with large OCT datasets. Compared with deeper CNN and transformer-based architectures, which often require greater computational resources and memory, the proposed framework provides a more balanced processing pipeline suitable for high-throughput clinical workflows. These characteristics enhance scalability by enabling rapid analysis of thousands of retinal scans with stable performance, making the framework appropriate for population-scale diabetic retinopathy and retinal disease screening programs while maintaining consistent diagnostic reliability across diverse imaging conditions.

The proposed framework demonstrates favorable resource utilization, which can result in lower energy consumption during practical deployment. By forwarding only clinically significant retinal regions to the deep feature extraction stage, the framework avoids unnecessary convolution operations over irrelevant background areas, thereby reducing computational workload and enhancing processing efficiency. This execution strategy is evidenced by a low overall inference time of 54 ms, with optimized processing stages of 17 ms for region of interest (ROI) localization, 24 ms for hierarchical feature extraction, and 13 ms for classification. As a result, the framework is anticipated to achieve higher throughput, lower processor utilization, reduced memory access, and improved energy efficiency compared to conventional end-to-end convolutional neural network (CNN) models that process entire optical coherence tomography (OCT) images. Furthermore, the combination of high precision (98.8%), recall (98.9%), F1-score (98.8%), low false positive rate (2.1%), and low false negative rate (1.6%) reduces the need for repeated clinical verification and unnecessary re-analysis, thereby enhancing operational efficiency. Collectively, these attributes suggest that RetinaFoldNet achieves a balanced optimization of diagnostic accuracy, computational efficiency, scalability, and resource awareness, offering a practical computer-aided diagnostic framework suitable for continuous clinical operation and future cloud- or edge-assisted ophthalmic healthcare systems.

CONCLUSION

This paper presented RetinaFoldNet, an intelligent deep learning framework for automated OCT-based retinal disease diagnosis that integrates anatomically guided retinal Region-of-Interest (ROI) localization with hierarchical multi-scale feature learning. By effectively emphasizing clinically significant retinal structures while suppressing redundant background information, the proposed framework achieved superior segmentation quality, accurate retinal localization, and robust multi-class disease classification. Experimental results demonstrated outstanding performance with an overall classification accuracy of 99.0\%, precision of 98.8\%, recall of 98.9\%, and F1-score of 98.8\%, consistently outperforming several representative state-of-the-art deep learning models while maintaining low computational latency. These findings demonstrate the effectiveness, reliability, and practical applicability of the proposed framework as a computer-aided decision-support system for retinal disease diagnosis. Future work will focus on validating the framework using multi-center and multi-device OCT datasets, incorporating explainable artificial intelligence for improved clinical interpretability, extending the framework to additional retinal pathologies through incremental learning, and exploiting three-dimensional OCT volume analysis to further enhance diagnostic accuracy and generalization.

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