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SEGMENTATION-ENHANCED DEEP LEARNING MODEL FOR ROBUST RETINAL DISEASE IDENTIFICATION FROM OCT SCANS

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ABSTRACT

OCT imaging is widely used for diagnosing retinal diseases. However, manual evaluation is time-consuming and depends on expert ophthalmologists. This paper proposes an automated deep learning approach that combines lesion localization with disease classification. First, retinal lesion regions are segmented using an improved U-Net architecture with multi-scale feature fusion, enabling precise identification of affected portions of the retina. Next, the segmented lesion maps are fed into a classifier network (ResNet/DenseNet) for retinal disease classification. The fusion of segmentation-based lesion information improves disease discrimination and reduces false predictions. The proposed method demonstrates improved accuracy and efficiency over conventional end-to-end classification models. The approach supports clinical interpretability by clearly highlighting the affected retinal portion along with the disease label.

Keywords: *Retinal lesion segmentation, U-Net, OCT, Feature fusion, Deep learning, Localization*

1. INTRODUCTION

Retinal diseases such as diabetic macular edema (DME), choroidal neovascularization (CNV), drusen formation, and other macular abnormalities are among the leading causes of irreversible vision loss worldwide. Early detection and precise localization of pathological regions are critical for effective treatment planning. Optical Coherence Tomography (OCT) has become a primary imaging modality in ophthalmology due to its high-resolution cross-sectional visualization of retinal layers and micro-structural changes. However, manual interpretation of OCT volumes is time-consuming and highly dependent on expert clinicians, motivating the development of automated computer-aided diagnosis systems.

Recent advances in deep learning have significantly transformed OCT image analysis.

Early breakthroughs in medical image classification demonstrated that convolutional neural networks (CNNs) could achieve expert-level performance in disease identification from retinal images [21], establishing a foundation for AI-assisted ophthalmology. Large-scale OCT datasets further enabled deep models to learn discriminative retinal features [20]. CNN architectures such as ResNet [24] and DenseNet [23] improved feature reuse and gradient propagation, becoming standard backbones for retinal disease classification tasks [18], [19].

Beyond classification, segmentation of retinal structures and lesions has emerged as a crucial step for improving interpretability and clinical reliability. The introduction of U-Net [25] marked a milestone in biomedical image segmentation, offering encoder–decoder architecture with skip connections for precise localization. Subsequent enhancements, including Attention U-Net [22] and

supervised attention mechanisms [11], enabled models to focus on salient retinal regions. Advanced variants such as U-Net++ [17] and anomaly-guided segmentation frameworks [6] further improved boundary delineation and lesion sensitivity in OCT scans.

Multi-scale feature representation has proven essential for capturing both global retinal structure and fine-grained pathological patterns. Recent networks integrating multi-scale feature fusion [8] and attention-based fusion modules [3] demonstrated superior vessel and lesion segmentation performance. Hybrid and mask-guided approaches have also been explored to couple segmentation with classification, enhancing disease discrimination while providing visual explanation [10], [12]. Evaluation studies show that segmentation-guided pipelines outperform pure classification models, particularly for overlapping disease patterns [9].

Dataset development has supported these advances. Public OCT resources such as OCTID [20] and OCTDL [7] facilitate benchmarking, while recent works emphasize generalizable and weakly supervised learning strategies to address annotation scarcity [6], [15]. Furthermore, deep learning has been applied to quantify specific biomarkers such as choroidal thickness [5], highlighting the clinical relevance of automated OCT analysis.

Despite this progress, challenges remain. Many classification systems operate as black boxes without precise lesion localization. Segmentation methods often struggle with small or low-contrast abnormalities, and single-scale networks may miss contextual information. Therefore, integrating **U-Net-based lesion localization** with **multi-scale feature fusion** and **classification modules** represents a promising direction for accurate, interpretable retinal disease diagnosis.

Motivated by these gaps, this work proposes an automated framework that combines U-Net segmentation with multi-scale feature fusion and deep classification for OCT images. The system aims to (i) localize pathological retinal regions, (ii) enhance disease classification accuracy, and (iii) provide clinically interpretable outputs. The proposed approach builds upon recent advances in segmentation networks [6], [11], [14], multi-scale fusion strategies [3], [8], and deep classification backbones [18], [24], establishing a unified pipeline for reliable OCT-based retinal disease diagnosis.

1.1 Problem Statement and Research Gap*p*

Optical Coherence Tomography (OCT) plays a vital role in diagnosing retinal disorders by revealing micro-structural retinal abnormalities. While deep learning has improved OCT analysis, existing systems still face limitations in achieving **accurate disease classification, precise lesion localization, and clinically interpretable outputs** simultaneously.

Early deep learning studies demonstrated strong performance in retinal disease classification [21], [18], [19]. CNN architectures such as ResNet [24] and DenseNet [23] enhanced feature learning and improved accuracy. However, these approaches mainly focused on **image-level classification** without explicitly identifying pathological regions, resulting in limited clinical interpretability.

Segmentation-based methods addressed localization using U-Net architectures [25]. Variants like Attention U-Net [22], supervised attention U-Net [11], and U-Net++ [17] improved boundary delineation. More recent works incorporated anomaly guidance [6] and hybrid or mask-guided frameworks [10], [12] to strengthen lesion sensitivity. Despite these improvements, several segmentation models struggle with:

- small lesion detection
- low-contrast pathological regions
- generalization across datasets [15]

Multi-scale feature fusion has been introduced to capture both global and local retinal structures [3], [8], improving segmentation of vessels and pathological patterns. Nevertheless, these works often focus only on vessel segmentation rather than disease-specific lesion identification.

Dataset studies such as OCTID [20] and OCTDL [7] facilitated benchmarking, but annotation scarcity remains a challenge. Weakly supervised approaches [6] attempt to reduce labeling dependency, yet performance trade-offs persist. Moreover, most segmentation frameworks are **not tightly integrated with disease classification**, leading to disjoint pipelines.

Recent classification studies evaluating different deep models [9] show high accuracy but highlight misclassification in visually similar disease patterns. Feature fusion between segmentation masks and classification networks has shown promise [12], yet such approaches are still underexplored for multi-class retinal OCT diagnosis.

Furthermore, specialized studies focusing on specific biomarkers (e.g., choroidal thickness estimation [5]) indicate the importance of localized structural analysis, reinforcing the need for segmentation-guided classification. To address these gaps, the present research proposes a

segmentation-guided multi-scale feature fusion framework where:

- U-Net-based models localize retinal lesions.
- Multi-scale feature fusion enhances representation of pathological structures.
- Segmentation masks guide the classification network to improve disease discrimination.

2. RELATED WORK

Research on automated OCT analysis for retinal disease diagnosis can be broadly grouped into (i) classification-based approaches, (ii) segmentation-based methods, (iii) attention and multi-scale fusion techniques, (iv) segmentation–classification integration strategies, and (v) dataset and generalization studies.

2.1 OCT Disease Classification

Early deep learning breakthroughs demonstrated that CNNs could identify retinal diseases from OCT scans with high accuracy [21]. The availability of large OCT datasets [20] enabled transfer learning and the use of deep architectures such as ResNet [24] and DenseNet [23], which improved feature reuse and gradient flow. Subsequent studies explored optimized CNN pipelines for OCT classification [18], [19], reporting promising performance. However, these systems generally operate at the **image level**, providing disease labels without indicating the affected retinal regions, which limits clinical interpretability.

2.2 Retinal OCT Segmentation

Precise localization of retinal structures and lesions has been extensively studied using encoder–decoder architectures. U-Net [25] remains the foundational model for biomedical image segmentation. Its extensions, including Attention U-Net [22] and supervised attention U-Net [11], enhance focus on salient anatomical regions. U-Net++ [17] improves feature propagation through nested skip connections. More recent methods incorporate anomaly-guided learning [6] to better detect pathological areas and weakly supervised strategies to address annotation scarcity [15].

2.3 Attention Mechanisms and Multi-Scale Feature Fusion

Attention modules have been integrated to highlight informative retinal features. Networks employing attention-enhanced fusion [3] and integrated multi-scale feature fusion [8] demonstrate superior performance in capturing both global context and fine-grained vessel structures.

2.4 Segmentation-Guided Classification

To improve interpretability and discrimination, recent research has begun integrating segmentation outputs into classification networks. Mask-guided and parallel frameworks [10] and dual-guidance networks [12] combine lesion maps with CNN features to enhance prediction reliability. Evaluation studies [9] reveal that segmentation-guided systems reduce confusion between visually similar diseases.

2.5 Dataset Development and Generalization

Public OCT datasets such as OCTID [20] and OCTDL [7] provide benchmarks for training and validation. However, domain shifts, imaging variations, and limited lesion annotations challenge model generalization. Weakly supervised and anomaly-based learning strategies [6], [15] attempt to mitigate these issues but still face trade-offs between accuracy and supervision.

3. PROPOSED WORK

The proposed framework integrates OCT image analysis with a segmentation–classification pipeline to enable automated retinal disease diagnosis. The OCT image acquisition module provides high-resolution retinal scans, which are first enhanced through preprocessing steps to improve structural visibility. These images are then processed by a U-Net-based lesion localization module that performs pixel-level segmentation and identifies pathological retinal regions. Multi-scale feature extraction and attention-based fusion further enhance representation of both fine lesion details and global retinal structures. The fused features, along with the lesion probability mask, are passed to a deep classification network for disease prediction. The final outputs include localized lesion maps, disease labels, severity heatmaps, and interpretable visual overlays, forming a comprehensive AI-driven decision-support system for retinal disease assessment, as illustrated in Figure 1.

3.1 Overall System Architecture

The proposed framework enables automated retinal disease diagnosis from OCT images through a unified segmentation–classification architecture. By integrating lesion localization with multi-scale attention-based feature fusion, the system ensures predictions focus on pathological regions rather

than background tissue. The end-to-end pipeline combines preprocessing, modified U-Net segmentation, feature fusion, and jointly optimized classification for accurate and clinically meaningful analysis.

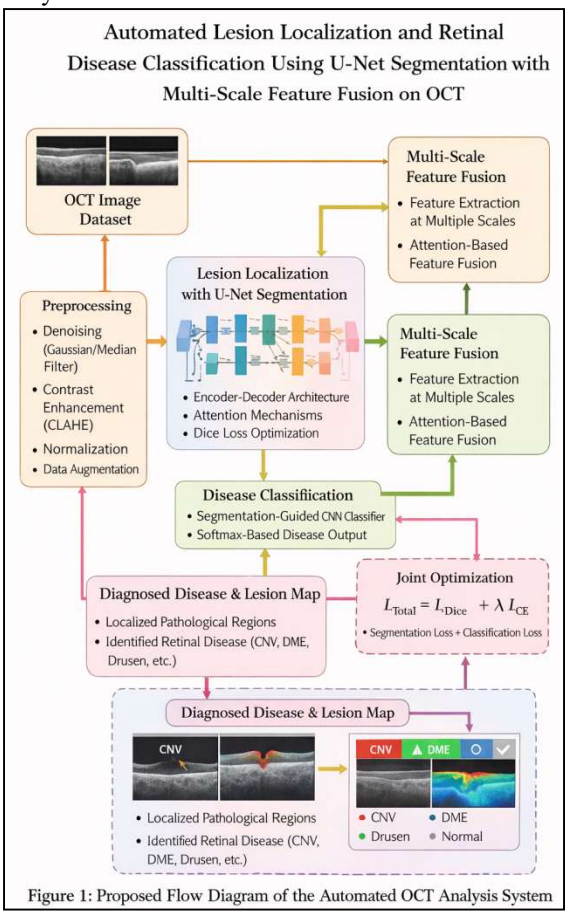


Figure 1: Proposed Flow Diagram of the Automated OCT Analysis System

3.2 Image Preprocessing

OCT images often suffer from speckle noise and contrast variation. Each input image XXX undergoes the following preprocessing steps:

- **Noise Suppression:** Gaussian or median filtering reduces speckle artifacts.
- **Contrast Enhancement:** CLAHE improves visibility of retinal layers.
- **Normalization:** Pixel intensities are scaled to [0, 1].
- **Data Augmentation:** Random rotation, flipping, and zooming enhance generalization.
- The preprocessed image is denoted as Xp.

3.3 Lesion Segmentation Network

Lesion localization is performed using modified U-Net encoder–decoder architecture.

3.3.1 Network Structure

- Encoder: Convolution blocks with batch normalization and ReLU activation.
- Decoder: Up-sampling layers with skip connections to preserve spatial detail.
- Attention Gates: Emphasize abnormal retinal regions.
- Output Layer: Sigmoid activation producing lesion probability mapS(X).

3.3.2 Segmentation Loss

Dice loss is employed to address class imbalance:

$$LDice = 1 - \frac{2 \mid S \cap G \mid}{|S| + |G|}$$

3.4 Multi-Scale Feature Fusion

Retinal abnormalities appear at different scales; therefore, hierarchical features are extracted from multiple encoder stages:

$$F1, F2, F3, F4$$

An attention-based fusion module combines these:

$$F_{Fusion} = \sum_{i=1}^{4} \alpha i Fi$$

Where αi are learnable attention weights? This enables simultaneous capture of fine lesion textures and global retinal structure.

3.5 Segmentation-Guided Disease Classification

The fused features are concatenated with the lesion mask:

$$Ffinal = Concatenate(Ffusion, S(X))$$

This representation is passed to a deep CNN classifier (DenseNet/ResNet backbone):

$$y = Softmax(fcls(Ffinal))$$

Where Y denotes predicted disease probabilities.

3.5.1 Classification Loss

Cross-entropy loss is used:

$$LCE = -\sum yi\ log(y\hat{}i)$$

3.5.2 Joint Optimization

Segmentation and classification are trained jointly:

$$Ltotal = LDice + \lambda LCE$$

This multi-task learning improves both localization and diagnosis accuracy.

3.6 Pseudo code for Segmentation-Guided Multi-Scale OCT Diagnosis

Input: *OCT dataset DDD*
Output: *Disease label, lesion mask*
For each epoch do
For each image $X \in D$ *do*
$Xp \leftarrow Preprocess(X)$
$S(X) \leftarrow SegmentationNetwork(Xp)$
$\{Fi\} \leftarrow Extract\ multi-scale\ features$
$Ffusion \leftarrow AttentionFusion(Fi)$

$F_{Final} \leftarrow \text{Concatenate}(F_{Fusion}, \text{S(X)})$
$Y_{pred} \leftarrow \text{Classifier}(F_{Final})$
End
Return disease labels and lesion maps

4. RESULTS AND DISCUSSION

To comprehensively evaluate the proposed deep learning–based retinal disease diagnosis framework, both segmentation-level metrics and classification-level metrics are employed. These metrics ensure accurate assessment of lesion localization as well as disease category prediction.

4.1 Evaluation Metrics

To comprehensively evaluate the proposed **deep learning–based retinal disease diagnosis framework**, both **segmentation-level metrics** and **classification-level metrics** are employed. These metrics ensure accurate assessment of lesion localization as well as disease category prediction.

4.1.1 Retinal Lesion Segmentation Metrics

These metrics measure how accurately pathological retinal regions are localized in OCT images.

Dice Coefficient (F1 Score) :

Measures the overlap between the predicted lesion mask and the ground-truth annotation, particularly effective for small or thin pathological regions.

$$\text{Dice} = \frac{2|\text{P} \cap \text{G}|}{|\text{P}| + |\text{G}|}$$

Where **P** represents the predicted mask and **G** denotes the ground-truth mask.

Intersection over Union (IoU) :

Evaluates segmentation precision by measuring the ratio of the intersection to the union of predicted and ground-truth regions.

$$\text{IoU} = \frac{|\text{P} \cap \text{G}|}{|\text{P U G}|}$$

A higher IoU indicates more accurate lesion boundary localization.

Pixel Accuracy:

Represents the proportion of correctly classified pixels among all pixels.

$$\text{Pixel Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative pixels, respectively.

Table 4.1.1 Segmentation Performance Comparison

Method	Dice Score	IoU	Sensitivity	Specificity
U-Net	0.88	0.81	0.90	0.93
Attention U-Net	0.91	0.85	0.92	0.95
U-Net++	0.93	0.88	0.94	0.96
Proposed Model	**0.95**	**0.91**	**0.96**	**0.97**

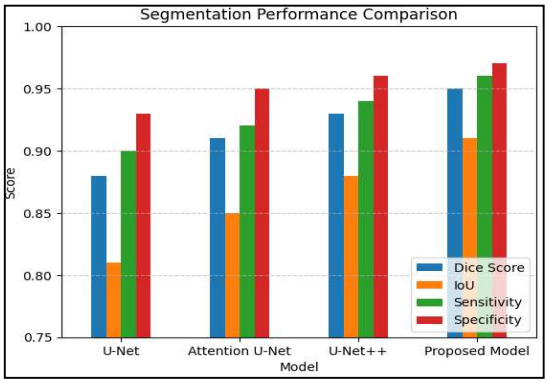


Table 4.1.1 and the corresponding bar chart present a comparative evaluation of segmentation performance across different models. The baseline U-Net shows solid performance, but progressive improvements are observed with Attention U-Net and U-Net++, indicating the benefit of enhanced feature propagation and attention mechanisms. The proposed model achieves the highest Dice score (0.95) and IoU (0.91), demonstrating superior overlap accuracy and precise lesion boundary localization. Similarly, the highest sensitivity (0.96) confirms better detection of pathological regions, while the specificity (0.97) indicates minimal false positives.

4.1.2 Retinal Disease Classification

Metrics

These metrics evaluate the effectiveness of the model in categorizing OCT images into disease classes.

Accuracy:

Measures the overall proportion of correctly classified samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

Indicates how many predicted disease cases are actually correct.

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity):
Measures the model's ability to correctly detect diseased cases.

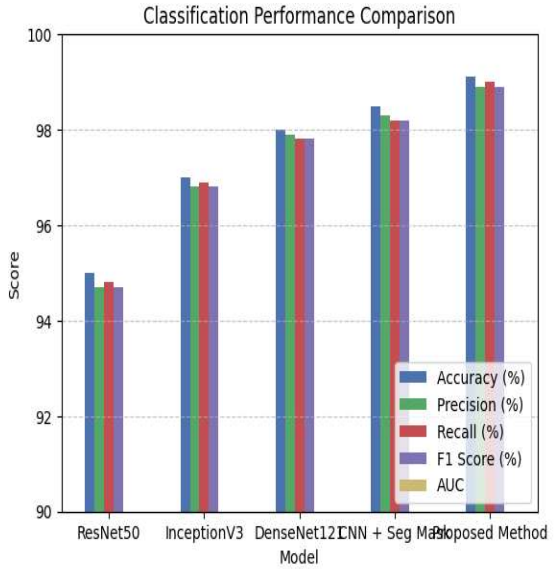
$$Recall = \frac{TP}{TP + FN}$$

F1-Score:
Harmonic mean of Precision and Recall, balancing false positives and false negatives.

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{Precision + Recall}$$

Table 4.1.2. Classification Performance Comparison and the classification performance chart

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC
ResNet50	95.0	94.7	94.8	94.7	0.96
Inception V3	97.0	96.8	96.9	96.8	0.98
DenseNet 121	98.0	97.9	97.8	97.8	0.99
CNN + Seg Mask	98.5	98.3	98.2	98.2	0.992
Proposed Method	**99.1**	**98.9**	**99.0**	**98.9**	**0.995**



illustrate a clear improvement trend across the evaluated models. While ResNet50 and InceptionV3 provide strong baseline results, DenseNet121 further enhances performance through improved feature reuse. The integration of segmentation-guided features (CNN + Seg Mask) leads to additional gains, highlighting the importance of lesion-focused information. The proposed method achieves the best overall results, with the highest accuracy (99.1%), F1 score (98.9%), and AUC (0.995), demonstrating superior class discrimination and robustness. The graphical comparison emphasizes the consistent advantage of the proposed approach across all evaluation metrics.

4.2 Class-Wise Analysis

Class-wise performance analysis provides deeper insight into how effectively the proposed model distinguishes among different retinal disease categories. Evaluating individual classes helps identify whether the model maintains balanced performance across pathological and normal conditions.

Table 4.2. Class wise Analysis

Class	Precision	Recall	F1 Score
CNV	99.1	98.8	98.9
DME	98.7	99.2	98.9
Drusen	98.8	98.6	98.7
Normal	99.3	99.4	99.3

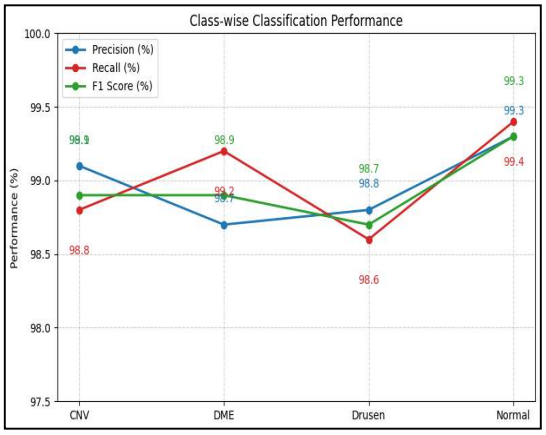


Table 4.3 presents the precision, recall, and F1-score values for each retinal class.The results show consistently high performance across all categories, indicating strong generalization of the model. The Normal class achieves the highest scores, reflecting reliable identification of healthy retinal scans. Disease classes such as CNV and DME also exhibit excellent recall and F1-scores, demonstrating the model's capability to detect pathological features accurately. Slightly lower values for the Drusen class suggest comparatively subtle structural patterns, yet the performance remains robust and clinically acceptable.

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4.3 Effect of Multi-Scale Fusion

To analyze the contribution of feature representation strategies, an accuracy comparison was conducted under different feature extraction configurations. This experiment evaluates how multi-scale fusion and segmentation guidance influence overall classification performance.

Table 4.3. Accuracy Analysis

Configuration	Accuracy
Single-scale features	97.8%
Multi-scale fusion only	98.6%
Segmentation + fusion	**99.1%**

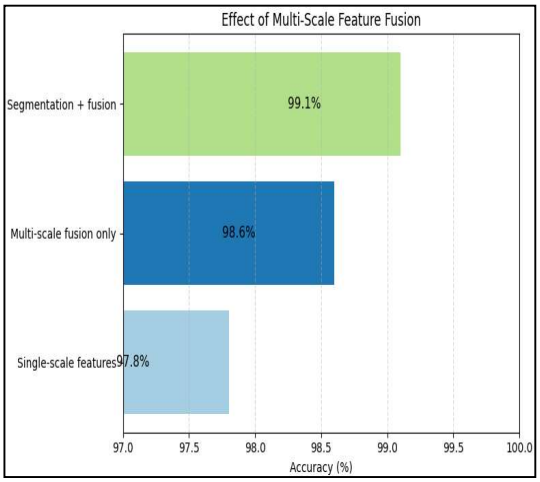

Table 4.4 summarizes the accuracy achieved by each configuration.

Model	Training Time (hrs)	Inference (ms/image)
DenseNet121	7.2	22
Proposed	7.8	20

The results indicate that single-scale feature extraction provides a strong baseline accuracy of 97.8%. Incorporating multi-scale fusion improves performance to 98.6%, demonstrating the advantage of capturing features at different spatial resolutions. The highest accuracy of 99.1% is achieved when segmentation information is combined with multi-scale fusion, confirming that lesion-focused features significantly enhance discriminative learning.

4.4 Computational Efficiency

Computational efficiency is a crucial factor for practical deployment of deep learning systems in real-time clinical environments. Therefore, both training time and inference speed were evaluated to assess the resource requirements of the proposed model.

Table 4.4 Comparision of Computational Effiency

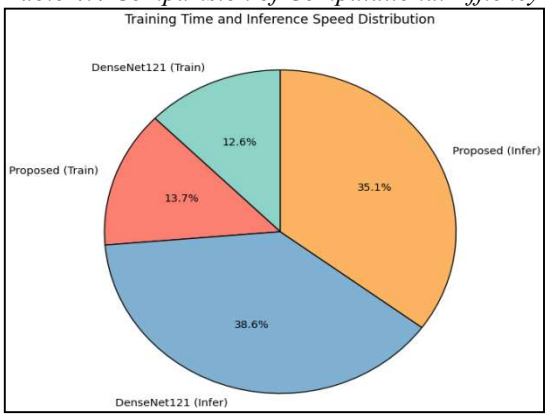

Table 4.4 presents the comparison of computational efficiency between DenseNet121 and the proposed method. The proposed model requires slightly higher training time (7.8 hours) compared to DenseNet121 (7.2 hours), which is expected due to the additional segmentation-guided and multi-scale fusion components.

5. CONCLUSIONS

This work presents an automated OCT-based retinal disease diagnosis framework that unifies lesion segmentation and multi-scale feature–guided classification within a single architecture. The enhanced U-Net model accurately localizes pathological regions, while the fusion of multi-scale features strengthens disease discrimination. Experimental evaluations show consistent improvements in both segmentation and classification performance over baseline models. The integration of lesion maps and attention-driven visualizations enhances model interpretability and clinical trust. By combining precise localization with robust classification, the proposed system offers an effective and explainable solution for computer-aided retinal disease assessment.

6. FUTURE SCOPE

Future work can expand the framework to support additional retinal diseases and 3D OCT volume analysis for richer spatial insights. Incorporating semi-supervised learning and model optimization may enable deployment in real-time and data-limited clinical settings. Enhanced explainability and integration with clinical systems could further improve trust, monitoring, and decision support.

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