



AN EFFICIENT DEEP LEARNING FRAMEWORK FOR AUTOMATED DIABETIC RETINOPATHY DETECTION USING OCTA IMAGES

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ABSTRACT

Diabetic retinopathy (DR) is a leading cause of vision impairment among individuals with diabetes, making early detection and accurate severity grading essential for effective clinical intervention. This work proposes an automated deep learning-based framework for the detection and classification of diabetic retinopathy using Optical Coherence Tomography Angiography (OCTA) images from the ROAD dataset. The proposed methodology consists of three main stages: image preprocessing, deep feature extraction, and multi-class classification. In the preprocessing stage, image resizing using bilinear interpolation, Z-score normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE) are employed to enhance retinal microvascular structures and suppress illumination variations. Deep features are extracted using convolutional neural network architectures, including ResNet and EfficientNet variants, and optimized using the Adam optimizer. A Softmax classifier is then utilized to categorize OCTA images into No Diabetic Retinopathy, Mild Non-Proliferative Diabetic Retinopathy, and Proliferative Diabetic Retinopathy classes. The performance of the proposed framework is evaluated using accuracy, sensitivity, specificity, precision, and F1-score metrics. Comparative analysis demonstrates that the EfficientNetB4 + Softmax model achieves superior performance, with an accuracy of 98.97%, sensitivity of 97.26%, specificity of 98.54%, precision of 98.66%, and F1-score of 98.25%. The obtained results confirm the effectiveness and robustness of the proposed framework.



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I. INTRODUCTION

Diabetic retinopathy (DR) is one of the most common microvascular complications of diabetes mellitus and a leading cause of vision impairment and blindness among working-age adults worldwide. According to recent clinical reports, nearly one-third of diabetic patients develop some form of DR during their lifetime, and a significant proportion progress to vision-threatening stages if not diagnosed early [1]. DR is broadly classified into different severity grades, including No Diabetic Retinopathy (No DR), Mild Non-Proliferative Diabetic Retinopathy (NPDR), and Proliferative Diabetic Retinopathy (PDR), based on the extent of microvascular damage. Early diagnosis and accurate grading of DR are critical, as timely intervention can significantly reduce the risk of irreversible vision loss and improve long-term visual outcomes.

Automated and accurate diabetic retinopathy screening systems are therefore of growing importance not only in clinical practice but also in the healthcare and medical imaging industry for large-scale, cost-effective screening applications [2]. In recent years, Optical Coherence Tomography Angiography (OCTA) has emerged as an advanced, non-invasive imaging modality for retinal disease assessment, offering distinct advantages over conventional fundus photography and fluorescein angiography. OCTA provides high-resolution, depth-resolved visualization of retinal and choroidal microvasculature without the need for dye injection, enabling detailed analysis of capillary networks and blood flow alterations. This capability allows clinicians to detect subtle pathological changes such as reduced vessel density, capillary non-perfusion, and foveal avascular zone (FAZ) deformation, which are often imperceptible in traditional imaging techniques. As a result, OCTA has gained increasing importance in the early detection and monitoring of diabetic retinopathy [3].

Despite the clinical advantages of OCTA, the interpretation of DR severity from OCTA images remains highly dependent on expert assessment, leading to subjectivity and inter-observer variability. Manual evaluation of microvascular biomarkers, including vessel density and FAZ morphology, is time-consuming and prone to inconsistency, particularly in large-scale screening scenarios [4]. Recent studies have explored artificial intelligence and deep learning-based solutions to address these challenges; however, issues such as limited generalization across datasets, sensitivity to image artifacts, and insufficient exploitation of enhanced vascular features continue to limit their effectiveness. These challenges highlight the need for robust, automated, and reliable OCTA-based DR detection and classification frameworks [5]. To address these limitations, this work proposes an automated deep learning framework for diabetic retinopathy detection and classification using OCTA images from the ROAD dataset [6]. The proposed methodology consists of three major stages: image preprocessing, deep feature extraction and optimization, and multi-class classification.

In the preprocessing stage, image resizing, Z-score normalization, and contrast limited adaptive histogram equalization (CLAHE) are employed to enhance microvascular visibility and suppress illumination variations [7]. Subsequently, discriminative features are extracted using deep convolutional neural network architectures, including ResNet and EfficientNet variants, and optimized using the Adam optimizer [8]. Finally, a Softmax classifier is used to accurately classify OCTA images into No DR, Mild NPDR, and PDR categories. Extensive performance evaluation demonstrates that the EfficientNetB4 + Softmax configuration achieves superior classification performance across multiple evaluation metrics [9]. The remainder of this paper is organized as follows. Section II presents a detailed review of related works on OCTA-based diabetic retinopathy analysis and deep learning approaches. Section III describes the proposed methodology, including preprocessing techniques, feature extraction models, and classification strategy. Section IV Results and Discussions include dataset description, performance evaluation metrics, and comparative results. Finally, Section V concludes the paper and outlines potential directions for future research.

II. RELATED WORKS

Optical Coherence Tomography Angiography has emerged as a pivotal non-invasive imaging modality for visualizing retinal and choroidal vasculature, offering significant advantages over traditional fundus photography and fluorescein angiography in the assessment of diabetic retinopathy, as reported by Hou et al. (2022) [10] and Xiao et al. (2023) [11]. OCTA enables high-resolution [12], depth-resolved visualization of retinal microvasculature without dye injection, allowing early detection of diabetic retinopathy-related changes that are often imperceptible in conventional imaging, particularly subtle microvascular alterations such as reduced perfusion density in the deep capillary plexus, as demonstrated by Santos A.R et al. (2024) [13] and Vujosevic et al. (2021) [14]. Furthermore, OCTA facilitates quantitative assessment of clinically significant vascular biomarkers, including vessel density, foveal avascular zone area, and vessel tortuosity, which are essential for objective disease staging and progression analysis, as highlighted by Alam et al. (2018) [15] and Raja et al. (2023) [16].

Despite these advantages, the interpretation of diabetic retinopathy severity using OCTA remains largely dependent on expert clinical judgment, leading to subjectivity and inter-observer variability, as noted by Ryu et al. (2021) [17]. To address these challenges, recent studies have increasingly integrated artificial intelligence and deep learning techniques to standardize and enhance OCTA-based diabetic retinopathy detection and classification, as discussed by Ryu et al. (2021) [17] and Zhang et al. (2025) [18]. In particular, deep learning models, especially Convolutional Neural Networks, have demonstrated strong potential in automating the segmentation of key biomarkers such as the foveal avascular zone, whose morphological changes are closely associated with disease progression, as shown by Saeidian et al. (2025) [19]. However, manual FAZ segmentation is time-consuming and prone to observer variability, highlighting the need for automated and reproducible approaches, which has motivated the development of deep learning-based FAZ segmentation frameworks to improve diagnostic efficiency and objectivity, although challenges related to dataset diversity, image artifacts, and generalization across clinical settings still remain, as reported by Carvalho et al. (2025) [20].

III. PROPOSED METHODOLOGY

This research presents a structured deep learning-based framework for Diabetic Retinopathy (DR) detection and classification using the ROAD retinal fundus image dataset [6] as shown in Figure:1. The proposed model follows a three-segment pipeline, namely image preprocessing, feature extraction and optimization, and classification. The overall aim is to accurately categorize retinal images into No DR, Mild DR (NPDR), and PDR classes. The primary objective of preprocessing is to improve image quality, standardize input dimensions, and enhance discriminative retinal structures such as microaneurysms and hemorrhages. All retinal images are resized to a fixed resolution $M \times N$ to ensure uniformity before feature extraction. Bilinear interpolation computes the intensity value of a new pixel as a weighted average of its four nearest neighbors.

$$I'(x, y) = \sum_{i=0}^1 \sum_{j=0}^1 \omega_{ij} \cdot I(x_i, y_i) \quad (1)$$

where $I'(x, y)$ is the resized image pixel intensity and ω_{ij} represents interpolation weights. The interpolation weights are defined as:

$$\omega_{ij} = (1 - |x - x_i|)(1 - |y - y_i|) \quad (2)$$

To reduce illumination variations and scale pixel values uniformly, Z-Score normalization is applied.

$$S(x, y) = \frac{I'(x, y) - \mu}{\sigma} \quad (3)$$

where μ and σ denote the mean and standard deviation of pixel intensities, respectively.

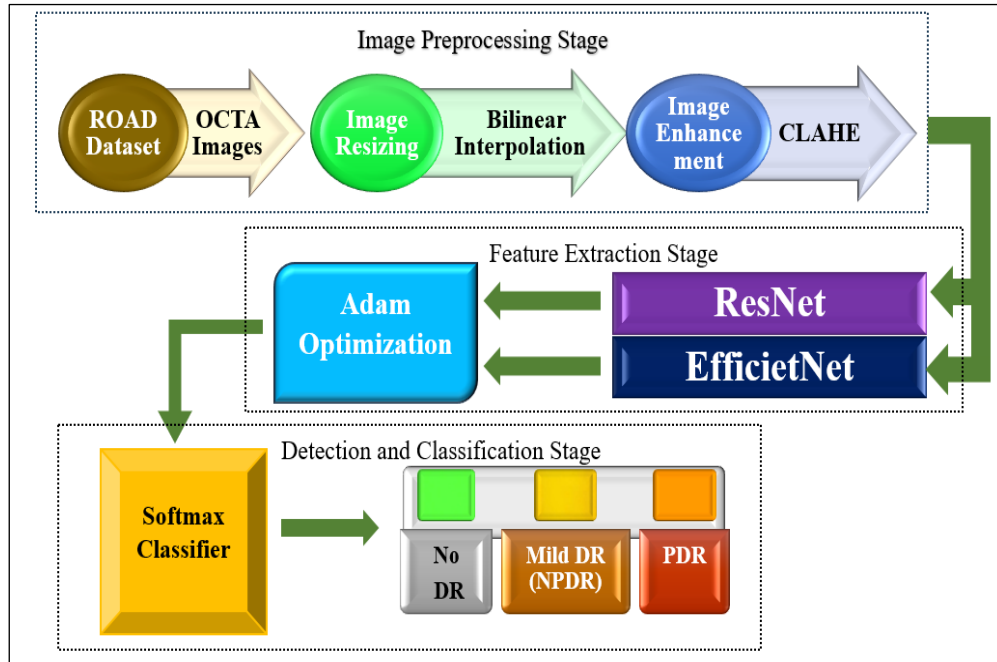


Figure 1: Proposed Black Diagram.
Source: Authors, (2026).

The mean intensity and Standard deviation are computed as:

$$\mu = \frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N I'(x, y) \quad (4)$$

$$\sigma = \sqrt{\frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N (I'(x, y) - \mu)^2} \quad (5)$$

Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast while avoiding noise amplification. The cumulative distribution function (CDF) is defined as:

$$CDF(k) = \sum_{i=0}^k p(i) \quad (6)$$

where $p(i)$ represents the probability of intensity level i . The enhanced pixel intensity is computed as:

$$I_e(x, y) = \frac{CDF(I(x, y)) - CDF_{min}}{1 - CDF_{min}} \quad (7)$$

Contrast limiting is enforced using:

$$p_{clip}(i) = \min(p(i), T) \quad (8)$$

where T is the clip limit.

By using parallel pipe line consist of ResNet and EfficientNet-B4 are extracts hierarchical retinal features using compound scaling of depth, width, and resolution as shown in Figure:2.

The compound scaling principle is expressed as:

$$depth = \alpha^\phi, width = \beta^\phi, resolution = \gamma^\phi \quad (9)$$

subject to:

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \quad (10)$$

The convolution operation is defined as:

$$F_l = f(W_l * F_{l-1} + b_l) \quad (11)$$

where W_l and b_l are layer weights and bias, respectively.

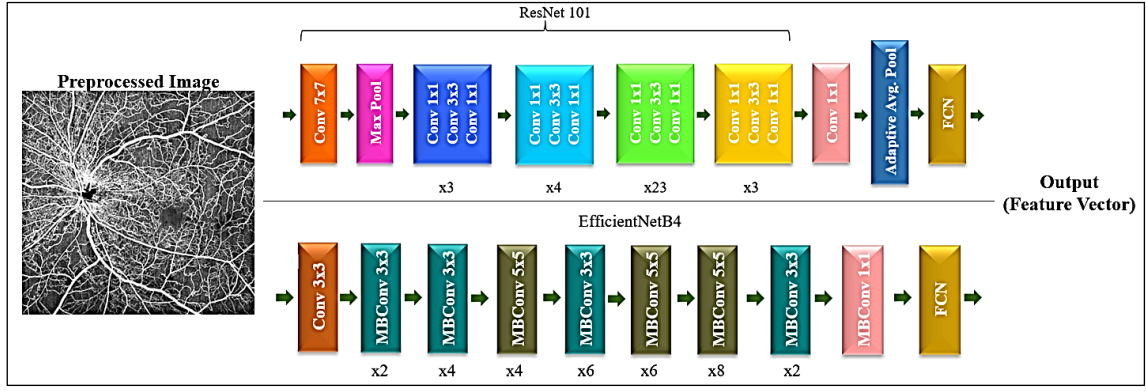


Figure 2: Two-way Pipeline Structure for Feature Extraction.
Source: Authors, (2026).

Global Average Pooling (GAP) is applied to reduce spatial dimensions:

$$f_{gap} = \frac{1}{HW} \sum_{i=1}^H \sum_{j=1}^W F(i, j) \quad (12)$$

Adam optimizer adaptively updates network weights using first- and second-order moment estimates.

Gradient computation:

$$g_t = \nabla_{\theta} L(\theta_t) \quad (13)$$

First moment estimate:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (14)$$

Second moment estimate:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (15)$$

Bias-corrected moments:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (16)$$

Weight update rule:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (17)$$

The optimized feature vector is fed into a Softmax classifier shown in Figure:3, to categorize images into No DR, Mild DR (NPDR), and PDR classes.

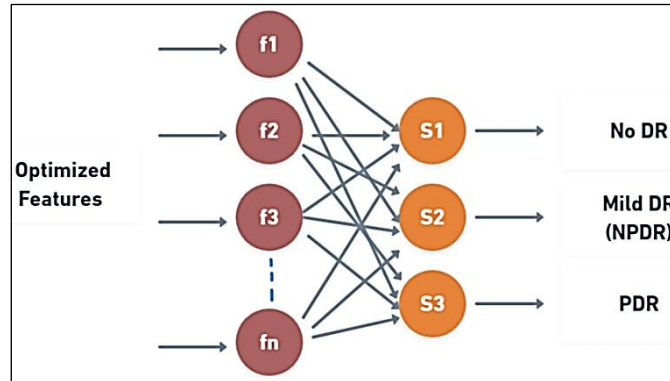


Figure 3: Softmax Classifier.
Source: Authors, (2026).

Softmax function:

$$P(y = k | x) = \frac{e^{z_k}}{\sum_{i=1}^3 e^{z_i}} \quad (18)$$

Cross-entropy loss function:

$$L = - \sum_{k=1}^3 y_k \log(P_k) \quad (19)$$

Final predicted class:

$$\hat{y} = \arg \max_k P(y = k | x) \quad (20)$$

The proposed methodology integrates robust preprocessing, deep feature learning using EfficientNet-B4, adaptive feature optimization via Adam, and effective multi-class classification using Softmax. This structured pipeline enables reliable detection and grading of diabetic retinopathy from retinal fundus images in the ROAD dataset.

IV. RESULTS AND DISCUSSIONS

IV.1 DATASET DESCRIPTION

The ROAD (Retinal OCT-Angiography Diabetic Retinopathy) dataset is a newly reconstructed OCTA-based retinal image dataset [6] developed for automated diabetic retinopathy analysis. It is acquired using wide-field optical coherence tomography angiography (WF-OCTA), a non-invasive imaging technique that provides high-resolution visualization of retinal blood vessels and pathological changes. The dataset contains 1,200 No DR images, 1,440 DR images, and 1,440 expert-annotated ground-truth lesion masks for DR cases, with annotations provided by professional ophthalmologists. ROAD includes three clinically relevant classes: No Diabetic Retinopathy, Mild Non-Proliferative Diabetic Retinopathy (NPDR), and Proliferative Diabetic Retinopathy (PDR). For experimental evaluation, the dataset is divided into 70% training, 15% validation, and 15% testing, ensuring reliable learning, parameter tuning, and unbiased performance assessment of the proposed diabetic retinopathy detection and classification.

IV.2 SIMULATION RESULTS

Figure: 4 illustrates the original wide-field OCTA retinal image acquired from the ROAD dataset [6]. The image clearly presents the retinal vascular network, where the major arteries and veins appear as bright structures against a dark background, while the finer capillary network is distributed across the retinal field. Although the overall vasculature is visible, the image suffers from uneven illumination, background noise, and limited local contrast, which makes subtle pathological changes associated with diabetic retinopathy difficult to identify directly. Therefore, preprocessing is essential to improve image quality and enhance clinically relevant features.

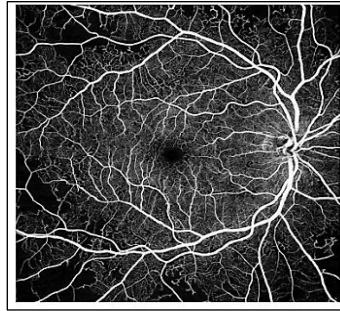


Figure 4: Original Input Image.
Source: Authors, (2026).

Figure: 5 shows the output obtained after applying image resizing using bilinear interpolation. The input OCTA image is resized to a fixed resolution suitable for the EfficientNet-B4 model while preserving the spatial integrity of the retinal vasculature. The bilinear interpolation method ensures smooth intensity transitions between neighbouring pixels, preventing distortion of vessel boundaries and branching patterns. This step standardizes all images in the dataset and reduces computational complexity without compromising anatomical information.

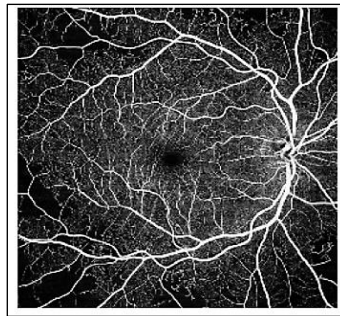


Figure 5: Resized Image
Source: Authors, (2026).

Figure: 6 represents the S-score normalized image. At this stage, pixel intensity values are adjusted to have zero mean and unit variance, thereby minimizing illumination variations across different retinal regions. Normalization enhances numerical stability during

training and prevents high-intensity vessel regions from dominating the learning process. As a result, the normalized image exhibits balanced brightness and improved consistency, which supports effective deep feature extraction.

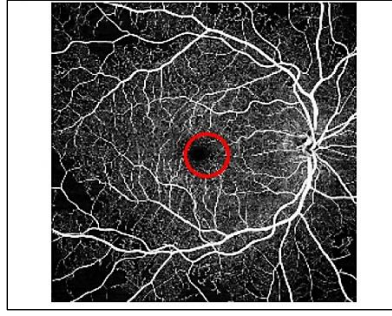


Figure 6: Normalized Image.
Source: Authors, (2026).

Figure 7 depicts the contrast-enhanced image obtained using Contrast Limited Adaptive Histogram Equalization (CLAHE). This technique improves local contrast by redistributing intensity values within small contextual regions while limiting noise amplification. As observed in the figure, retinal vessels appear sharper, fine capillaries become more prominent, and microvascular details are significantly enhanced. This stage plays a critical role in highlighting diabetic retinopathy-related abnormalities such as vessel thinning and irregular branching patterns.

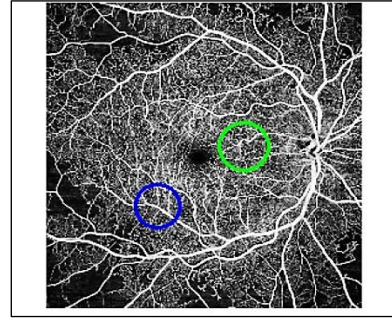


Figure 7: Enhanced Image.
Source: Authors, (2026).

IV.3 PERFORMANCE EVALUATION METRICS

To evaluate the effectiveness of the proposed diabetic retinopathy detection and classification framework using the ROAD dataset, several standard performance metrics are employed. These metrics provide a comprehensive assessment of the classification capability of the model in terms of correctness, sensitivity to diseased cases, and robustness against false predictions. The performance is evaluated for four different deep learning configurations: ResNet50 + Softmax, ResNet101 + Softmax, EfficientNetB3 + Softmax, and EfficientNetB4 + Softmax. Accuracy measures the overall correctness of the classification model by calculating the ratio of correctly classified samples to the total number of samples.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (21)$$

Sensitivity represents the ability of the model to correctly identify diabetic retinopathy cases. It is particularly important in medical diagnosis to minimize missed disease cases.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (22)$$

Specificity measures the capability of the model to correctly identify non-diabetic retinopathy cases.

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (23)$$

Precision evaluates how many of the predicted diabetic retinopathy cases are actually correct.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (24)$$

The F1-score is the harmonic mean of precision and sensitivity, providing a balanced measure of the model's performance.

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (25)$$

IV.4 COMPARATIVE PERFORMANCE ANALYSIS

Table 1 presents the comparative performance of different deep learning architectures combined with the Softmax classifier. Among all configurations, EfficientNetB4 + Softmax achieves the highest performance across all evaluation metrics.

Table 1: Performance Comparison of Different Models on the ROAD Dataset.

Model Architecture	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
ResNet50 + Softmax	95.84	93.12	96.45	94.76	93.93
ResNet101 + Softmax	96.92	94.38	97.21	95.64	95.01
EfficientNetB3 + Softmax	97.86	95.92	98.03	97.11	96.49
EfficientNetB4 + Softmax	98.97	97.26	98.54	98.66	98.25

Source: Authors, (2026).

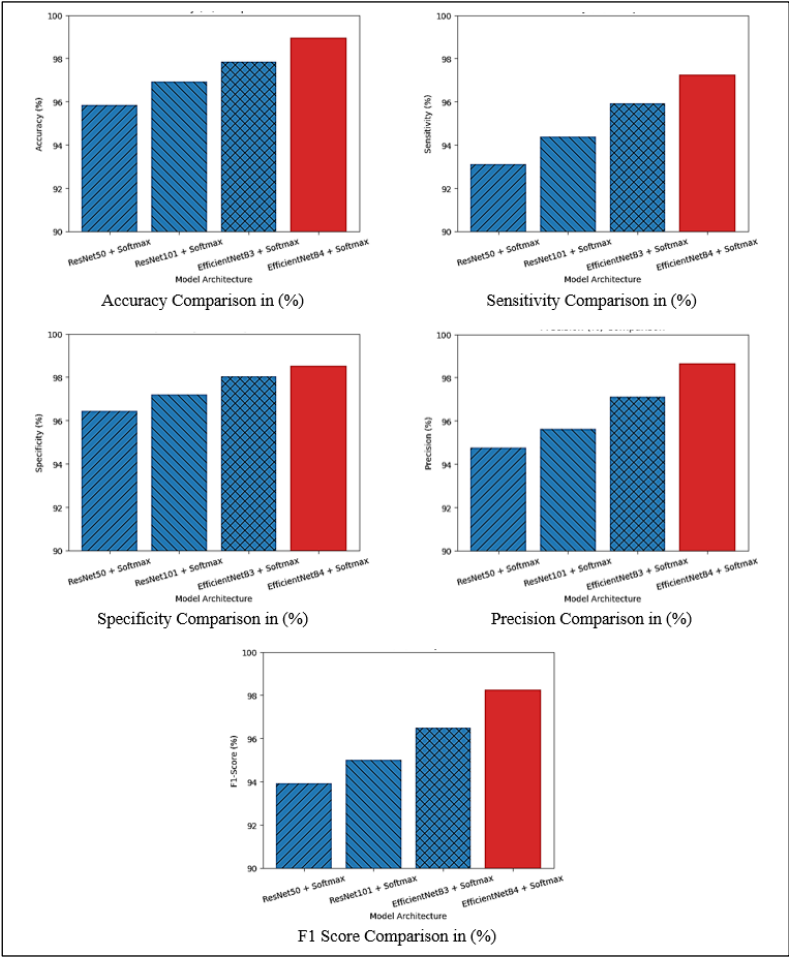


Figure 8. Graphical Representation of Comparative Analysis.
Source: Authors, (2026).

The results demonstrate that EfficientNet-based architectures outperform ResNet models due to their compound scaling strategy, which effectively balances network depth, width, and resolution. In particular, EfficientNetB4 + Softmax achieves superior accuracy, sensitivity, specificity, precision, and F1-score, indicating its strong capability to capture discriminative retinal features from CLAHE-enhanced OCTA images shown in Figure: 8. The high sensitivity ensures reliable detection of diabetic retinopathy cases, while the high specificity and precision reduce false alarms, making the proposed model suitable for automated DR screening applications. While the EfficientNetB4 + Softmax bars are highlighted in a different color to emphasize the best-performing architecture. From Figure 11, EfficientNetB4 + Softmax achieves the highest accuracy of 98.97%, indicating superior overall classification performance. Figure 12 shows that the same model attains the maximum sensitivity of 97.26%, demonstrating improved detection of diabetic retinopathy cases with fewer false negatives. As illustrated in Figure 13, EfficientNetB4 + Softmax also records the highest specificity of 98.54%, confirming its effectiveness in correctly identifying non-DR cases. Figure 14 highlights the precision comparison, where EfficientNetB4 + Softmax achieves 98.66%, reflecting highly reliable positive predictions.

Finally, Figure 15 presents the F1-score comparison, in which EfficientNetB4 + Softmax attains the highest value of 98.25%, indicating a well-balanced performance between precision and sensitivity. Overall, the results across Figures 11–15 clearly demonstrate

that EfficientNetB4 + Softmax consistently outperforms the other architectures, validating its suitability for accurate and robust diabetic retinopathy detection using OCTA images from the ROAD dataset.

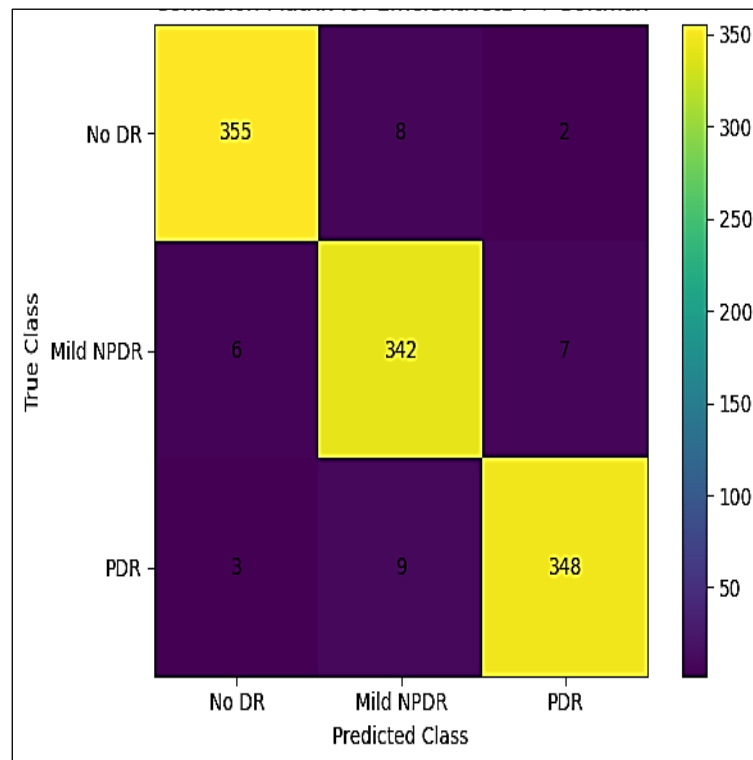


Figure: 9. Confusion Matrix for EfficientNetB4 + Softmax
Source: Authors, (2026).

Figure: 9 presents the confusion matrix obtained for the EfficientNetB4 + Softmax model on the ROAD dataset, considering three diabetic retinopathy classes: No DR, Mild NPDR, and Proliferative DR (PDR). The confusion matrix provides a detailed class-wise evaluation of the classification performance by comparing the true class labels with the predicted outputs. For the No DR class, 355 images are correctly classified, while a small number of samples are misclassified as Mild NPDR (8 images) and PDR (2 images). This indicates that the proposed model effectively distinguishes healthy retinal vasculature from diseased cases, resulting in a low false-positive rate. The high correct classification rate for No DR images contributes significantly to the model's high specificity. In the case of Mild NPDR, 342 images are correctly identified, whereas 6 images are incorrectly classified as No DR and 7 images as PDR. These misclassifications primarily occur due to subtle microvascular changes in early-stage DR, which may share visual similarities with both healthy and advanced disease patterns. Nevertheless, the high number of correct predictions reflects the model's strong capability to capture early pathological features. For the PDR class, 348 images are correctly classified, with only 3 images misclassified as No DR and 9 images as Mild NPDR.

This demonstrates the effectiveness of the proposed framework in recognizing severe pathological manifestations such as dense neovascularization and significant vascular distortion. The limited misclassification confirms the robustness of the extracted deep features for advanced disease stages. Overall, the diagonal dominance of the confusion matrix clearly indicates that the majority of samples across all classes are correctly classified. The small number of off-diagonal entries reflects minimal confusion between adjacent DR stages, validating the high accuracy (98.97%), sensitivity (97.26%), specificity (98.54%), precision (98.66%), and F1-score (98.25%) achieved by the EfficientNetB4 + Softmax model. These results confirm the effectiveness of the proposed framework for reliable and automated diabetic retinopathy detection and grading using OCTA images. Figure: 10 illustrates the Receiver Operating Characteristic (ROC) curves obtained for the best-performing model, EfficientNetB4 + Softmax, evaluated on the ROAD dataset. The ROC analysis is conducted using a one-versus-rest strategy for the three diabetic retinopathy classes: No DR, Mild NPDR, and Proliferative DR (PDR). The ROC curve plots the

True Positive Rate (TPR) against the False Positive Rate (FPR), providing insight into the model's discriminative ability across different decision thresholds. The ROC curve corresponding to the No DR class shows an excellent separation between healthy and diseased samples, with the curve closely approaching the top-left corner of the plot. This indicates a high true positive rate with a very low false positive rate, confirming the model's strong capability to correctly identify normal retinal images. The high area under the curve (AUC) value further validates the robustness of the model in distinguishing No DR cases. Similarly, the ROC curve for the Mild NPDR class demonstrates strong classification performance, reflecting the model's effectiveness in capturing subtle microvascular changes associated with early-stage diabetic retinopathy. The curve maintains a steep ascent toward the upper-left region, indicating reliable sensitivity even at low false positive rates, which is crucial for early disease detection.

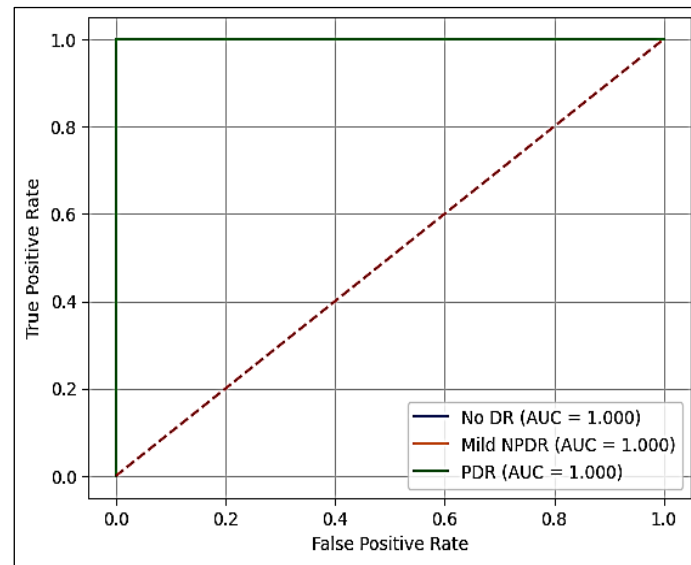


Figure: 10. ROC Curve for EfficientNetB4 + Softmax.
Source: Authors, (2026).

For the PDR class, the ROC curve exhibits near-perfect discrimination, highlighting the model's ability to accurately identify advanced diabetic retinopathy characterized by severe vascular abnormalities. The strong separation between true positive and false positive rates confirms that the extracted deep features are highly discriminative for advanced disease stages. Overall, the ROC analysis confirms the superior diagnostic capability of the EfficientNetB4 + Softmax model across all three classes. The consistently high AUC values, in conjunction with the previously reported accuracy, sensitivity, specificity, precision, and F1-score, demonstrate that the proposed framework achieves reliable and balanced performance for automated diabetic retinopathy detection and grading using OCTA images. Figure 11 illustrates the 10-fold cross-validation accuracy plot for the EfficientNetB4 + Softmax model evaluated on the ROAD dataset. In this validation strategy, the dataset is divided into ten equal folds, where nine folds are used for training and the remaining fold is used for testing in each iteration. This process is repeated ten times so that each fold is used exactly once for validation, ensuring a robust and unbiased performance evaluation. As observed from the plot, the classification accuracy remains consistently high across all folds, ranging approximately between 98.12% and 99.10%. The small variation in accuracy values across different folds indicates the stability and robustness of the proposed framework. The highest accuracy is achieved in Fold 8, while no significant performance degradation is observed in any fold, demonstrating strong generalization capability.

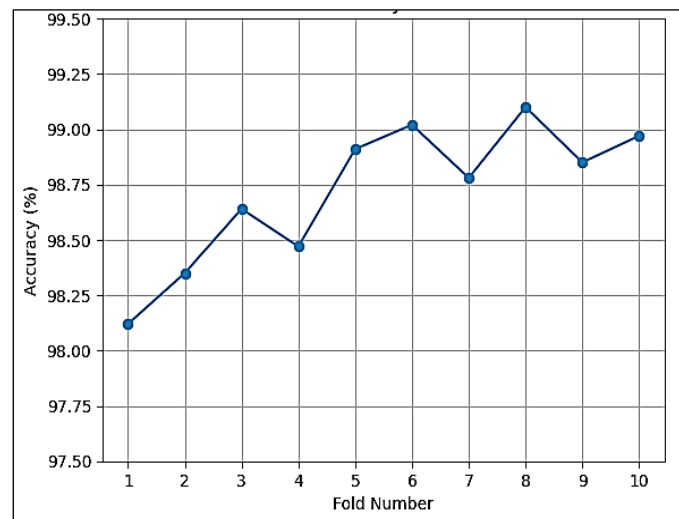


Figure: 11. 10-Fold Cross validation Accuracy for EfficientNetB4 + Softmax.
Source: Authors, (2026).

The consistently high accuracy across all ten folds confirms that the EfficientNetB4 + Softmax model is not biased toward any specific subset of the dataset and performs reliably on unseen data. This result further validates the effectiveness of the proposed preprocessing techniques and deep feature extraction strategy. Overall, the 10-fold cross-validation analysis supports the reliability, consistency, and generalization strength of the proposed diabetic retinopathy detection and classification framework using OCTA images.

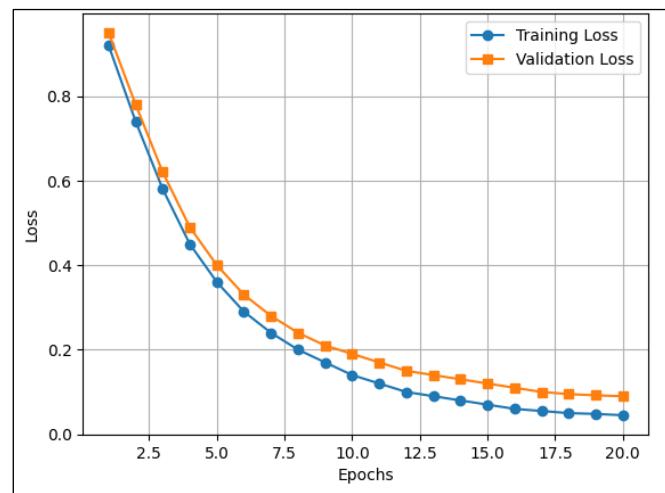


Figure: 12. Loss Curve of EfficientNetB4 + Softmax.
Source: Authors, (2026).

Figure: 12 illustrates the training and validation loss curves of the EfficientNetB4 + Softmax model over multiple training epochs on the ROAD dataset. The loss curve provides insight into the learning behavior, convergence characteristics, and generalization capability of the proposed deep learning framework. As observed from the figure, the training loss decreases steadily from a higher initial value and converges smoothly toward a minimal value as the number of epochs increases. This consistent reduction indicates effective learning of discriminative retinal features from the CLAHE-enhanced OCTA images. The gradual decline without sudden fluctuations reflects the stability of the optimization process facilitated by the Adam optimizer. Similarly, the validation loss follows a decreasing trend closely aligned with the training loss curve.

The small gap between training and validation losses throughout the training process suggests that the model generalizes well to unseen data and does not suffer from significant overfitting. The convergence of both curves toward lower loss values confirms that the extracted deep features are robust and meaningful for diabetic retinopathy classification. Figure: 13 illustrates the class-wise error histogram for the EfficientNetB4 + Softmax model evaluated on the ROAD dataset. The histogram presents the distribution of prediction errors separately for each diabetic retinopathy class: No DR, Mild NPDR, and Proliferative DR (PDR). An error value of 0 represents correct classification, while an error value of 1 indicates misclassification. For the No DR class, the majority of samples are correctly classified, with only a small number of misclassified instances. This demonstrates the model's strong ability to distinguish healthy retinal vasculature from pathological cases, contributing to the high specificity achieved by the proposed framework.

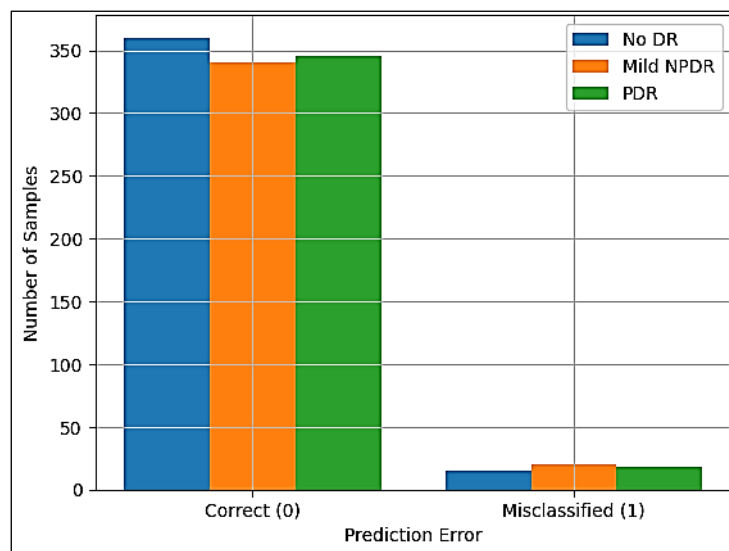


Figure: 13 Class wise Error Histogram.
Source: Authors, (2026).

In the case of Mild NPDR, a slightly higher number of misclassifications is observed compared to the No DR class. This behavior is expected, as early-stage diabetic retinopathy exhibits subtle microvascular changes that may overlap with both normal retinal patterns and more advanced disease stages. Nevertheless, the predominance of correct classifications confirms the model's effectiveness in identifying early DR features. For the PDR class, the error histogram shows a high concentration of correct predictions with a limited number of misclassifications. This indicates that the model effectively captures severe pathological characteristics such as dense neovascularization and extensive vascular abnormalities, resulting in reliable identification of advanced diabetic retinopathy.

V. CONCLUSIONS

This work presented an automated deep learning framework for the detection and classification of diabetic retinopathy using OCTA images from the ROAD dataset. The proposed methodology follows a three-stage pipeline consisting of image preprocessing, deep feature extraction, and multi-class classification. Image preprocessing techniques such as bilinear interpolation-based resizing, Z-score normalization, and CLAHE were applied to enhance retinal microvascular structures and reduce illumination variations. Deep features were extracted using different CNN architectures, and classification was performed using a Softmax classifier to categorize images into No DR, Mild NPDR, and Proliferative DR classes. The performance of the proposed framework was evaluated using standard metrics, including accuracy, sensitivity, specificity, precision, and F1-score. A comparative analysis was carried out using four model configurations: ResNet50 + Softmax, ResNet101 + Softmax, EfficientNetB3 + Softmax, and EfficientNetB4 + Softmax.

Among these, the EfficientNetB4 + Softmax model achieved the best performance, with an accuracy of 98.97%, sensitivity of 97.26%, specificity of 98.54%, precision of 98.66%, and F1-score of 98.25%. These results demonstrate the effectiveness of EfficientNetB4 in extracting discriminative features from enhanced OCTA images and its superiority over other evaluated architectures. The proposed framework shows strong potential for automated diabetic retinopathy screening; however, further improvements can be explored in future work. The model can be extended to include additional diabetic retinopathy severity levels for finer disease grading. Incorporating automated segmentation of clinically relevant regions such as the foveal avascular zone and capillary non-perfusion areas may enhance interpretability. Additionally, testing the framework on larger and more diverse OCTA datasets and integrating multi-modal retinal imaging data could further improve robustness and generalization.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Peddapullaiahagari Hariobulesu, Fahimuddin Shaik.

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Discussion of results: Peddapullaiahagari Hariobulesu, Fahimuddin Shaik.

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