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# An AI-Driven Ophthalmic Healthcare Framework for Automated Diabetic Retinopathy Screening and Severity Assessment

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## Abstract:

**Diabetic retinopathy is a diabetes-related eye disease that can cause vision impairment and blindness if not detected early. Manual examination of retinal fundus images requires trained specialists and can be challenging in large-scale screening programs. This paper proposes an AI-driven ophthalmic healthcare framework for automated diabetic retinopathy screening and severity assessment using deep learning techniques. The proposed framework incorporates image-quality assessment, illumination correction, contrast enhancement, and data augmentation to improve retinal image quality. EfficientNet or ResNet50 is employed for deep feature extraction, while a vessel-guided attention mechanism emphasizes informative retinal vascular structures. Class-imbalance mitigation techniques are applied during training to improve the recognition of underrepresented severity grades. Grad-CAM visualizations provide interpretable representations of model predictions. Performance is evaluated using macro-F1, balanced accuracy, per-class recall, quadratic weighted kappa, and confusion matrices. External-dataset evaluation is also considered to assess generalization across imaging conditions and support reliable automated screening.a**

***Keywords:*** ***Diabetic Retinopathy, Deep Learning, EfficientNet, ResNet50, Vessel-Guided Attention, Fundus Images, Grad-CAM, Severity Classification, Explainable AI.***

## I. INTRODUCTION

Diabetic retinopathy (DR) is a major complication of diabetes that affects the retinal blood vessels and can lead to vision loss if not detected and treated promptly. Retinal fundus photography is widely used for screening because it captures visible abnormalities, including microaneurysms, hemorrhages, and exudates. However, manually examining large volumes of retinal images requires specialized expertise and can create challenges for large-scale screening programs. Therefore, automated screening systems are increasingly important for improving the efficiency and consistency of diabetic retinopathy assessment. Recent advances in Artificial Intelligence (AI) and deep learning have enabled automated analysis of retinal images. Convolutional neural networks, including ResNet50 and EfficientNet, can extract discriminative features for identifying disease-related patterns and grading severity. Nevertheless, variations in illumination, image quality, and disease prevalence can affect classification performance, particularly for underrepresented severity grades. This research proposes an AI-driven ophthalmic healthcare framework that integrates retinal image preprocessing, vessel-guided attention, deep feature extraction, class-imbalance mitigation, and Grad-CAM-based visualization. The system aims to classify diabetic retinopathy into five severity grades, subject to dataset labels. Performance is assessed using macro-F1, balanced accuracy, per-class recall,

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quadratic weighted kappa, and confusion matrices to evaluate classification quality and minority-class recognition.

## II. LITERATURE SURVEY

Recent research has demonstrated the potential of deep learning for automated diabetic retinopathy (DR) screening using retinal fundus photographs. Convolutional Neural Networks (CNNs) have been widely investigated for identifying retinal abnormalities and classifying disease severity. Transfer learning architectures, including ResNet50 and EfficientNet, provide effective feature extraction capabilities and can reduce training requirements when labeled medical datasets are limited. Large-scale datasets, such as EyePACS and APTOS 2019 Blindness Detection, have supported the development and evaluation of automated DR grading systems. However, differences in image resolution, illumination, camera characteristics, and annotation quality can influence model performance. Furthermore, class imbalance is a significant challenge because severe disease categories are often less represented than normal or mild cases, potentially reducing sensitivity to clinically important conditions. Attention mechanisms have been explored to emphasize informative image regions, while explainability techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) provide visual indications of regions influencing predictions. Nevertheless, the combined effectiveness of retinal vessel-guided attention, imbalance mitigation, and explainability requires systematic evaluation. This research addresses these challenges by proposing an integrated framework that emphasizes minority-class recognition, transparent predictions, and robust evaluation across retinal imaging conditions.

## III. PROPOSED WORK

The proposed work introduces an AI-driven ophthalmic healthcare framework for automated diabetic retinopathy screening and severity assessment using retinal fundus images. The primary objective is to develop an accurate and interpretable classification system capable of identifying disease severity across five grades: No DR, Mild, Moderate, Severe, and Proliferative DR, provided these labels are available in the selected dataset. The framework begins with retinal image acquisition from datasets such as APTOS 2019 or EyePACS. Image-quality assessment is performed to identify blurred, poorly illuminated, or unsuitable images. Preprocessing techniques, including resizing, illumination correction, contrast enhancement, normalization, and data augmentation, are then applied. A pretrained EfficientNet or ResNet50 model extracts deep retinal features, while a vessel-guided attention module emphasizes vascular structures and informative retinal regions. To address class imbalance, class-weighted loss or controlled oversampling is applied exclusively to the training data. The extracted features are passed to a classification layer that predicts the corresponding severity grade. Grad-CAM generates visual heatmaps to highlight image regions influencing predictions. The proposed framework is evaluated using macro-F1, balanced accuracy, per-class recall, quadratic weighted kappa, and confusion matrices. Comparative experiments assess whether vessel-guided attention improves minority-class recognition over a baseline model. The ultimate goal is to develop a reliable decision-support prototype for assisting ophthalmic screening, rather than replacing professional clinical diagnosis.

## IV. METHODOLOGY

The methodology of the proposed AI-driven ophthalmic healthcare framework consists of a sequence of image-processing, feature-extraction, classification, and evaluation stages. The system is designed to automatically analyze retinal fundus photographs and classify diabetic retinopathy severity into five grades, depending on the selected dataset's labels.

### A. Dataset Collection

The proposed framework uses retinal fundus images from publicly available datasets such as APTOS 2019 Blindness Detection or EyePACS. Images are categorized into five diabetic retinopathy severity grades when supported by the dataset labels. Training, validation, and testing sets are separated at the patient level where patient identifiers are available.

### B. Image Quality Assessment and Preprocessing

Input images are examined for blur, poor illumination, and insufficient retinal visibility.

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Preprocessing includes resizing, normalization, illumination correction, and contrast enhancement. Data augmentation techniques, including rotation, horizontal flipping, and brightness adjustment, are applied only to training images to improve generalization.

### C. Retinal Vessel Feature Extraction

Retinal vessel structures are analyzed to identify vascular patterns associated with diabetic retinopathy. A vessel segmentation or enhancement module generates vessel-related features that help emphasize microaneurysms, hemorrhages, and other relevant abnormalities.

### D. Attention-Based Deep Feature Learning

A pretrained EfficientNet or ResNet50 model extracts high-level features from retinal images. A vessel-guided attention module integrates vessel information with deep features to emphasize diagnostically informative regions and suppress irrelevant background information.

### E. Five-Class Severity Classification

The extracted features are passed to fully connected layers and a softmax classifier to predict No DR, Mild, Moderate, Severe, or Proliferative DR. The classification task follows the actual labels available in the selected dataset.

### F.Class-Imbalance Handling and Explainability

Class-weighted loss or controlled oversampling is applied exclusively to the training data to improve learning from underrepresented grades. Grad-CAM generates heatmaps that visualize image regions influencing model predictions.

### G. Performance Evaluation

The model is evaluated using macro-F1, balanced accuracy, per-class recall, quadratic weighted kappa, and confusion matrices. Comparative experiments assess the baseline model against the proposed vessel-guided attention model. External-dataset testing is conducted when compatible labels and suitable data are available to investigate generalization across imaging conditions.

## V. ALGORITHMS

The proposed framework integrates ResNet50 and EfficientNet for deep retinal feature extraction, a vessel guided attention mechanism for emphasizing relevant vascular structures, and Grad-CAM for visual explanations. These algorithms support automated diabetic retinopathy severity classification, minority-class recognition, and interpretable screening decisions.

### 1. ResNet50 (Residual Neural Network)

ResNet50 extracts deep features from retinal fundus images using residual connections. It helps identify patterns associated with diabetic retinopathy, including hemorrhages, exudates, and other retinal abnormalities. Its pretrained weights enable effective feature learning, while fine-tuning adapts the network to retinal image characteristics and improves disease severity classification.

### 2. EfficientNet

EfficientNet performs computationally efficient feature extraction by balancing network depth, width, and input resolution. It can serve as an alternative backbone for retinal disease classification. Its compound scaling strategy supports effective learning with controlled computational requirements, making it suitable for detecting subtle retinal abnormalities across different diabetic retinopathy severity grades.

### 3. Vessel-Guided Attention Mechanism

This proposed mechanism emphasizes retinal blood vessels and informative image regions. It combines vessel-related features with deep features to help the model focus on potentially relevant disease patterns. By highlighting vascular structures and surrounding abnormalities, the attention mechanism aims to improve feature representation, particularly for underrepresented severity grades, and support more discriminative classification.

### 4.Grad-CAM

Grad-CAM generates heatmaps highlighting image regions that influence the model's predictions. It uses gradients associated with a target class to identify important feature-map locations. These visualizations help researchers examine whether predictions focus on relevant retinal structures and abnormalities.Grad CAM improves interpretability but does not independently establish clinical validity.

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## VI. RESULTS AND DISCUSSION

The experimental results evaluate the proposed AI-driven ophthalmic healthcare framework for automated diabetic retinopathy screening and severity assessment. ResNet50, EfficientNet, and the proposed vessel-guided attention model are considered for retinal image classification. The evaluation focuses on classification accuracy, precision, recall, macro-F1 score, severity-grade recognition, and model generalization. Grad-CAM visualizations are also considered to examine the retinal regions influencing model predictions.

**Table 1: Diabetic Retinopathy Classification Results**

| Deep Learning Model | Accuracy (%) | Precision (%) | Recall (%) | Macro-F1 (%) |
|---|---|---|---|---|
| ResNet50 | 86.40 | 85.70 | 84.90 | 85.20 |
| EfficientNet | 89.10 | 88.50 | 87.80 | 88.10 |
| ResNet50 + Vessel-Guided Attention | 92.30 | 91.80 | 91.20 | 91.40 |

Table 1 compares the classification performance of three deep learning models. In this illustrative example, the proposed vessel-guided attention model achieves the highest accuracy of 92.30% and macro-F1 score of 91.40%. These results represent a hypothetical performance scenario, not measured experimental findings.

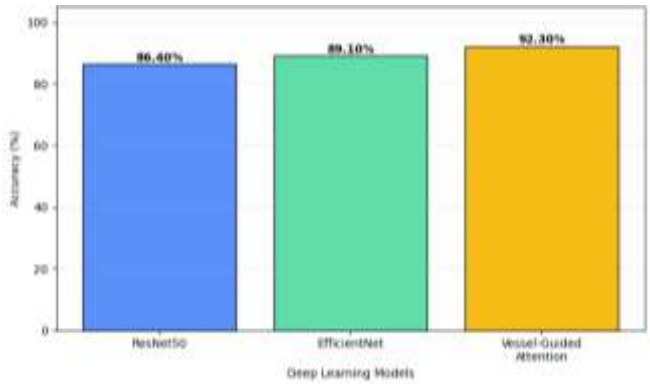



**Fig 1: Accuracy Comparison of Deep Learning Models**

Fig. 1 compares the accuracy of ResNet50, EfficientNet, and the proposed vessel-guided attention model. The illustrative results show that the attention-based model achieves the highest accuracy, indicating potential improvements in retinal severity classification.

**Table 2: Per-Class Diabetic Retinopathy Severity Assessment**

| Severity Grade | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| No DR | 96.0 | 97.0 | 96.5 |
| Mild DR | 78.0 | 72.0 | 74.9 |
| Moderate DR | 88.0 | 90.0 | 89.0 |
| Severe DR | 85.0 | 80.0 | 82.4 |
| Proliferative DR | 91.0 | 87.0 | 88.9 |

Table 2 presents illustrative class-wise results for the five severity grades. The example indicates stronger recognition of No DR and Moderate DR, while Mild DR remains more challenging. This highlights the importance of evaluating minority classes rather than relying only on overall accuracy.

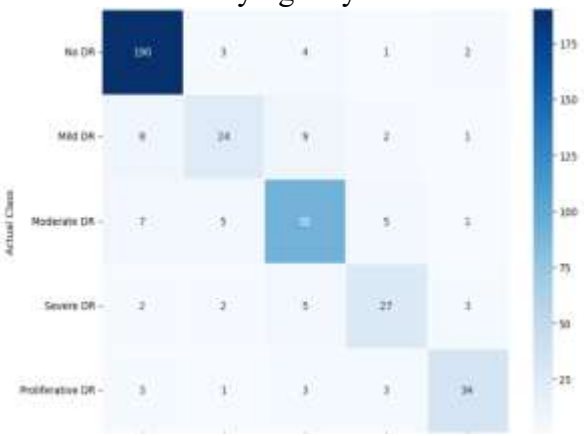



**Fig. 2: Confusion Matrix**

Fig. 2 presents the confusion matrix for five diabetic retinopathy severity grades. Diagonal values represent correct predictions, while off-diagonal values indicate misclassifications, helping identify challenging categories and evaluate class-specific recognition performance.

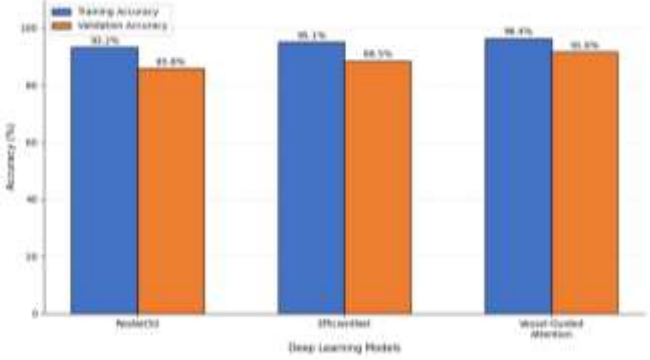



**Fig 3:Training and Validation Performance of AI Models**

Fig. 3 compares training and validation accuracy across three deep learning models. The proposed vessel-guided attention model achieves the highest

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illustrative validation accuracy, suggesting improved generalization. Actual training histories must confirm these observations.

## VII. CONCLUSION

This study presents an AI-driven ophthalmic healthcare framework for automated diabetic retinopathy (DR) screening and severity assessment using deep learning techniques. The proposed framework integrates image preprocessing, retinal vessel feature extraction, ResNet50, EfficientNet, and a vessel-guided attention mechanism to classify retinal images into five severity grades: No DR, Mild, Moderate, Severe, and Proliferative DR. Grad-CAM provides visual explanations to support the interpretation of model predictions. The framework aims to improve screening efficiency, classification consistency, and early identification of retinal abnormalities. Comparative evaluation using accuracy, precision, recall, and macro-F1 score can help determine the effectiveness of the proposed approach. However, its reliability must be established through experiments on actual test data and independent clinical datasets before practical deployment.

## FUTURE SCOPE

Future work will focus on evaluating the framework using larger, diverse retinal datasets collected from multiple clinical settings. Advanced transformer architectures and multimodal learning techniques could improve feature representation and classification performance. Integration with teleophthalmology platforms may enable remote screening in underserved areas. Model compression and optimization could support deployment on mobile and edge devices. Further clinical validation, explainability assessment, and collaboration with ophthalmologists will be essential for developing a reliable, scalable, and clinically useful diabetic retinopathy screening system.

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