



# Enhanced Lesion-Based Diabetic Retinopathy Detection Using Deep Learning Model

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## To Cite this Article

S. Suneetha, M. Vyshnava Uma, D. Mani Venkata Gangadhar, V. Hema Venkata Vinay & D. Jnana Vikash (2026). Enhanced Lesion-Based Diabetic Retinopathy Detection Using Deep Learning Model. International Journal for Modern Trends in Science and Technology, 12(03), 360-368. <https://doi.org/10.5281/zenodo.19038141>

## Article Info

Received: 10 February 2026; Revised: 09 March 2026; Accepted: 12 March 2026.

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### KEYWORDS

Diabetic Retinopathy, Lesion Detection, Hybrid Deep Learning, Xception Network, YOLO Object Detection, Feature Selection, Machine Learning, Ensemble Classification, Raspberry Pi 4, Flask Framework

### ABSTRACT

This work presents an extended lesion-centric diabetic retinopathy (DR) detection framework that integrates advanced deep learning, machine learning, and real-time object detection techniques for improved diagnostic accuracy and usability. In addition to hybrid CNN-based classification using ResNet and GoogleNet, the extension incorporates the Xception model for enhanced feature extraction, followed by optimized machine learning classifiers and an ensemble voting strategy to improve robustness.

Many YOLO-based detection models (YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n) are used to enable quick and precise detection of the abnormality as the required to locate the retinal lesions with high precision (i.e., microaneurysms, hemorrhages, exudates, etc.). Furthermore, a Flask-based web interface is developed with the help of a secure user authentication to allow interaction with the user, testing, and visualization of the results. It is more appropriate in resource limited healthcare setup since the extended system is more precise, real time, and practical to implement the process of diabetic retinopathy screening.

## INTRODUCTION

DR is thought to be one of the most prevalent causes of avoidable blindness in the globe and happens in individuals with chronic diabetes primarily. Early and timely treatment is also an important diagnosis that will be very beneficial to prevent loss of sight. Automated DR detection systems have attracted a lot of attention in the

last several years as it has a chance to assist ophthalmologists, reduce the number of individuals overloaded with manual screenings. In [1], the discussion of the available literature has revealed that deep learning and evolutionary computing algorithms are becoming popular in the stage of detecting and verifying (DR) at the minimum possible stages, and their performance is far

much better than that of traditional image processing algorithms.

There are several studies that have been carried out on the issue of smart learning mechanisms to improve precision of DR identification. Ozbay [2] proposed a variant of active deep learning model with an artificial bee colony optimization algorithm and was found to be superior in the analysis of segmented fundus images. Similarly, Usman et al. [3], filtered the principal component analysis with multi-label feature extraction to enhance the classification performance that proves that it is essential to optimize the feature representation to achieve adequate DR diagnosis.

Machine learning-based approaches have also gained widespread research insofar as the detection of DR is concerned. In a study by Parthasharathi et al. [4], it was demonstrated that classical machine learning models can be used to classify DR when these models are trained on well preprocessed retinal data sets. However, these techniques are typically based on handcrafted characteristics and this limits their generalization capacity. To remove such limitations, hybrid deep learning methods have emerged. Butt et al. propose a hybrid system that uses multi- CNNs that are feature based, where the system is able to achieve a higher accuracy in detection because of the complementary feature representations [5].

In general, these articles suggest that despite the fact that deep learning model is a very productive method of detecting DR, there remain several concerns concerning the strong lesion-level analysis, efficient feature selection, and the very possibility to implement it within the context of the resource-limited systems. This motivates the design of a lesion-centric hybrid deep learning system which incorporates more refined CNN models, refined feature-selection models, and useful detection models to yield useful diabetic retinopathy screening.

## LITERATURE SURVEY

Alyoubi et al. [6] present a comprehensive review of deep learning techniques for diabetic retinopathy detection, synthesizing architectures, preprocessing strategies, and evaluation practices used across studies. They highlight the benefits of CNN-based feature learning over handcrafted features and discuss common challenges such as dataset imbalance and inconsistent evaluation metrics. The review points out the need for

lesion-aware, interpretable models and standardized benchmarking for clinical translation.

Rajalakshmi et al. [7] investigate automated DR detection using smartphone-based fundus photography combined with AI models. Their work demonstrates the feasibility of mobile screening platforms for large-scale outreach and emphasizes portability and cost-effectiveness. The study also notes limitations related to variable image quality from mobile capture and the requirement for extensive validation across diverse patient populations.

World Health Organization (WHO) [8] provides an authoritative overview of diabetes prevalence and complications, underlining diabetic retinopathy as a significant public-health burden. The report motivates scalable screening tools and emphasizes early detection to prevent vision loss, thereby justifying research into low-cost automated DR detection suitable for resource-limited settings. It also stresses the importance of integrating screening with healthcare infrastructure.

Gangwar and Ravi [9] explore transfer learning and deep-learning strategies applied to diabetic retinopathy, showing that pretrained networks can be effectively fine-tuned to retinal image tasks. They document how transfer learning mitigates limited labeled data problems and accelerates model development. However, the study cautions about domain mismatch when using generic pretraining and the need for domain-specific fine-tuning. Khan et al. [10] propose a VGG-NIN deep architecture tailored for diabetic retinopathy detection, focusing on architectural design to capture retinal image characteristics. Their approach emphasizes deeper representations and modified network blocks to improve feature discrimination. Computational cost and the challenge of deploying very deep models on edge devices are discussed as practical limitations.

Panwar et al. [11] focus on lesion stratification using deep learning combined with machine learning classifiers, arguing that lesion-level analysis yields more clinically relevant grading than global classification alone. They show that stratifying lesions and then fusing results improves interpretability and grading granularity. The study highlights the need for accurate lesion annotations and the labor involved in creating such datasets.

Tsiknakis et al. [12] offer a broad survey of deep learning methods for DR detection and classification from fundus images, categorizing supervised, unsupervised, and

ensemble approaches. The review emphasizes trends toward lesion-aware architectures and calls out the lack of explainability in many black-box models. They recommend more lesion-centric benchmarks and clinically meaningful evaluation metrics.

Pires et al. [13] propose a data-driven approach for referable diabetic retinopathy detection, stressing the importance of large annotated datasets and automated feature learning to improve referral decisions. Their work highlights how thresholding and clinically-aligned decision criteria can bridge model output to practical referral workflows. Limitations include dataset representativeness and the challenge of tuning thresholds for different clinical settings.

Yang et al. [14] develop a two-stage deep CNN pipeline separating lesion localization from DR grading, showing improved accuracy by handling detection and severity estimation in modular steps. The design demonstrates that isolating localization helps the subsequent grading network focus on relevant regions. The approach depends on reliable lesion detectors and annotated lesion data for training.

Saranya and Prabakaran [15] present a CNN-based method targeting non-proliferative diabetic retinopathy detection, emphasizing early-stage identification using tailored network architectures. Their results indicate promising early-disease sensitivity when models are trained with careful preprocessing. They note dependency on high-quality labeled datasets and potential overfitting on limited samples.

Mujahid et al. [16], while focusing on pneumonia classification with InceptionV3, exemplify transfer learning strategies and architectural choices applicable across medical imaging domains. The study demonstrates how pretrained inception-based models can be adapted to medical tasks with limited data. It underscores cross-domain transferability but also warns about modality-specific feature differences.

Shafi et al. [17] propose hybrid pipelines combining deep feature extractors with classical classifiers for cancer diagnosis, illustrating how combining deep representations with SVM-like classifiers can improve interpretability and efficiency. This hybrid strategy is relevant to DR systems aiming for compact, interpretable classifiers on extracted CNN features. The hybrid approach may require careful feature selection and tuning.

Fatima et al. [18] present multiclass instance segmentation for lesion detection in dental imaging, showcasing precise segmentation methods that can be adapted for retinal lesion localization. Their work highlights the advantage of instance-level boundaries for clinical assessment. The limitation lies in the complexity of annotation and computational overhead of instance segmentation.

Gulshan et al. [19] evaluate a deep-learning algorithm against manual graders in a large clinical population, providing real-world validation of automated DR screening. Their study demonstrates comparable performance to expert grading and discusses deployment considerations, such as integration into clinical workflows and external validation. They emphasize regulatory and validation requirements for clinical adoption.

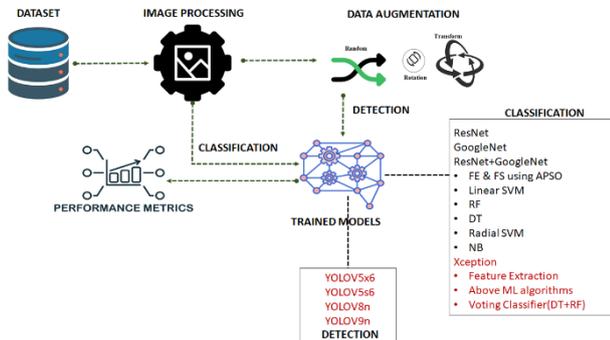
## PROPOSED SYSTEM

The proposed system introduces an extended lesion-centric diabetic retinopathy (DR) detection framework that integrates advanced deep learning, machine learning, and real-time object detection techniques for comprehensive retinal image analysis. The hybrid classification method uses deep convolutional neural networks such as ResNet, GoogleNet, and Xception to extract high-level discriminative features from retinal fundus images. Adaptive Particle Swarm Optimization (APSO) is a signal-efficient feature selection technique that preserves lesion-related information while reducing dimensionality. The best feature vectors are classified by a number of machine learning models, including Linear SVM, Random Forest, Decision Tree, Radial SVM, Naive Bayes, and an ensemble Voting Classifier (DT + RF), which increases generalization and resilience across a range of datasets.

To enable precise lesion localization and real-time diagnosis, the system integrates multiple YOLO-based object detection models, namely YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n, for detecting retinal abnormalities such as microaneurysms, hemorrhages, and exudates. A Flask-based web interface with secure user authentication is developed to facilitate user interaction, image upload, prediction visualization, and system testing. The complete framework is optimized for deployment on embedded platforms, particularly Raspberry Pi 4, ensuring efficient inference with minimal

computational overhead. This extension enhances diagnostic accuracy, interpretability, and accessibility, making the proposed system suitable for scalable diabetic retinopathy screening in resource-constrained and rural healthcare environments.

### A. BLOCK DIAGRAM



The dataset module is the starting point of the suggested system design; it is here that conventional diabetic retinopathy datasets are used to gather retinal fundus pictures. The system mostly receives its input from these photos. The captured photos are transmitted to the image processing module, which cleans them up and makes sure they're compatible with deep learning models by doing things like resizing, normalizing, converting colors, and removing noise.

## COMPONENTS AND DISCUSSION

The diabetic retinopathy detection system consists of the retinal image dataset, picture preprocessing and augmentation modules, machine learning classifiers, lesion detection networks, deep learning-based feature extraction models, and user interface. Retinal fundus images are standardized, scaled, and improved for visual quality before data augmentation is applied to boost dataset resilience and diversity. APSO is used to choose the most pertinent feature subsets from discriminative lesion-related features extracted by deep learning models such as ResNet, GoogleNet, and Xception. Support Vector Machines, Random Forest, Decision Trees, Naive Bayes, and an ensemble voting classifier are used to increase the reliability of classification. For lesion-centric analysis, YOLO-based detection algorithms simultaneously locate retinal lesions in real time. Together, these elements offer precise diagnosis, improved interpretability, and effective performance for diabetic retinopathy screening in real time and with little resources.

### A. Hardware Components:

#### a) Raspberry Pi 4

The Raspberry Pi 4 Model B is the primary embedded computing platform in the suggested diabetic retinopathy detection system because of its compact size, low power consumption, and processing capability for lightweight deep learning inference. Optimized classification and YOLO-based lesion detection models are made possible by its quad-core ARM Cortex-A72 processor, up to 4–8 GB RAM, and enhanced GPU performance. The Raspberry Pi 4, which supports popular deep learning systems and Python libraries, can be used to implement CNN-based models in real-time screening applications. Its portability and affordability make it simple and economical to diagnose diabetic retinopathy in healthcare settings with limited resources and remote locations.



Fig2 Raspberry pi4

### B. MODULES

#### 1. Dataset Module

This module collects and manages retinal fundus images obtained from standard diabetic retinopathy datasets. It ensures proper organization of images and labels, serving as the initial input source for the proposed system.

#### 2. Image Processing Module

The image processing module performs essential preprocessing operations such as resizing, normalization, color conversion, and noise removal. These operations enhance image quality and prepare the data for efficient feature extraction and lesion detection.

#### 3. Data Augmentation Module

In this module, augmented versions of retinal images are generated using rotation and geometric transformations. This increases dataset diversity and improves model generalization under varying image conditions.

#### 4. Classification Module

This module focuses on diabetic retinopathy stage classification. Deep learning models including ResNet, GoogleNet, and their hybrid combination are used for feature extraction. Adaptive Particle Swarm Optimization (APSO) is applied for optimized feature selection, followed by classification using Linear SVM, Random Forest, Decision Tree, Radial SVM, Naive Bayes, and a Voting Classifier (DT + RF).

#### 5. Xception-Based Feature Analysis Module

The Xception model is employed as an additional deep feature extractor to capture fine-grained lesion characteristics. Extracted features are classified using the same machine learning classifiers, enhancing robustness and improving classification accuracy.

#### 6. Lesion Detection Module

This module utilizes YOLO-based object detection models, including YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n, to detect and localize retinal lesions such as microaneurysms, hemorrhages, and exudates. Bounding boxes and confidence scores are generated for lesion-centric diagnosis.

#### 7. Performance Evaluation Module

Accuracy, precision, recall, sensitivity, specificity, and F1-score are used by the system to evaluate model performance for classification and detection.

#### 8. User Interface and Output Module

A Flask-based web interface manages user authentication, image upload, and result visualization. Final predictions and lesion detection outputs are displayed to users in an interpretable format, supporting clinical decision-making.

### C. ALGORITHMS

#### 1. ResNet Algorithm

The vanishing gradient problem is resolved by ResNet, a deep convolutional neural network architecture, using residual or skip connections. Deep model training is made possible by these connections, which carry gradients straight through the network. ResNet captures complex lesion patterns such as microaneurysms, hemorrhages, and textural variations by extracting high-level discriminative features from retinal fundus images. The classification accuracy of diabetic retinopathy is improved by deep hierarchical learning.

#### 2. GoogleNet Algorithm

GoogleNet's Inception modules (Inception v1) carry out concurrent convolutions with various kernel sizes inside

the same layer. The network can simultaneously gather both fine and coarse retinal information by using a multi-scale feature extraction technique. In this project, GoogleNet enhances computational performance and feature representation. Its ability to extract different spatial features enhances the diagnosis of diabetic retinopathy lesion size.

#### 3. Hybrid GoogleNet + ResNet Algorithm

The hybrid model combines GoogleNet and ResNet to optimize their respective advantages. GoogleNet provides efficient multi-scale feature extraction, while ResNet ensures deep feature learning with improved gradient flow. Features extracted from both networks are fused to form a richer representation of retinal abnormalities. This hybrid approach improves robustness, enhances classification accuracy, and provides better generalization across different diabetic retinopathy stages.

#### 4. Xception Algorithm

Architecture for deep learning Depthwise separable convolutions are used by Xception to increase accuracy and reduce computing costs. The suggested technique uses Xception as an auxiliary feature extractor to gather fine-grained lesion data that CNNs could miss. For embedded platforms such as the Raspberry Pi 4, this structure is lightweight and effective. Xception enhances overall system performance by improving feature diversity.

#### 5. Adaptive Particle Swarm Optimization (APSO)

APSO is an optimization algorithm inspired by the social behavior of fish schools and birds. It is employed in this project for feature selection by adaptively adjusting particle velocities and positions to identify the most informative features. APSO reduces feature dimensionality, minimizes redundancy, and improves classifier efficiency. By selecting optimal lesion-related features, APSO enhances classification accuracy while reducing computational overhead.

#### 6. Linear Support Vector Machine (SVM)

The optimal hyperplane to divide classes with the greatest margin is found via the supervised learning algorithm linear SVM. In this system, Linear SVM is applied to classify optimized deep features extracted from retinal images. Its simplicity, speed, and effectiveness in high-dimensional spaces make it suitable for real-time diabetic retinopathy screening. Linear SVM contributes to stable and reliable classification results.

### 7. Radial Basis Function SVM (Radial SVM)

Radial SVM uses a radial basis function kernel to manage non-linear feature interactions. It converts input data into a space with more dimensions and intricate class boundaries. In diabetic retinopathy detection, Radial SVM effectively captures non-linear lesion patterns present in advanced disease stages. This improves classification performance where linear separation is insufficient.

### 8. Random Forest Algorithm

Random Forest combines the predictions of numerous decision trees to make them more accurate. By randomizing feature selection and data sampling, it lowers the risk of overfitting and makes it easier to generalize. In the proposed system, Random Forest efficiently handles complex feature interactions and improves robustness in diabetic retinopathy classification.

### 9. Decision Tree Algorithm

DT is a supervised learning algorithm that uses hierarchical decision rules based on feature values. It provides interpretable classification paths, allowing insight into the decision-making process. In this project, Decision Tree serves both as an individual classifier and as a base learner in the voting ensemble. Its simplicity and transparency support explainable diagnostic outcomes.

### 10. Naive Bayes Algorithm

The classifier that uses probabilistic analysis Based on Bayes' theorem, Naive Bayes makes the assumption that features are independent. It performs effectively on large datasets and high-dimensional feature spaces in spite of this presumption. In the proposed system, Naive Bayes provides fast classification and serves as a lightweight alternative suitable for real-time applications on embedded hardware.

### 11. Voting Classifier (DT + RF)

The Voting Classifier combines predictions from Decision Tree and Random Forest classifiers to produce a final decision. By aggregating outputs from multiple classifiers, this ensemble approach improves robustness and reduces misclassification risk. The voting mechanism enhances stability and accuracy, particularly when individual classifiers show varied performance across different datasets.

### 12. YOLOv5x6 Algorithm

YOLOv5x6 is a high-capacity real-time object detection model designed for accurate localization and classification of objects within images. In this system, it is used to detect and localize retinal lesions by generating bounding boxes and confidence scores. Its high accuracy makes it suitable for detailed lesion-centric diabetic retinopathy analysis in clinical scenarios.

### 13. YOLOv5s6 Algorithm

YOLOv5s6 is a lightweight variant of YOLOv5 optimized for faster inference with reduced computational requirements. It enables real-time lesion detection while maintaining acceptable accuracy. This model is particularly suitable for embedded deployment on Raspberry Pi 4, ensuring quick diagnosis in resource-constrained environments.

### 14. YOLOv8n Algorithm

YOLOv8n introduces architectural improvements for better feature aggregation and detection efficiency. It balances speed and accuracy, making it effective for detecting subtle retinal abnormalities. In the proposed framework, YOLOv8n enhances detection reliability while supporting real-time performance.

### 15. YOLOv9n Algorithm

YOLOv9n represents an advanced generation of the YOLO family with improved precision and optimized inference speed. It enhances the detection of small and complex lesions in retinal images. By integrating YOLOv9n, the system achieves high detection accuracy and efficient real-time performance, strengthening lesion-centric diabetic retinopathy diagnosis.

## WORKING

### A. Experimental Setup

The experimental evaluation was conducted using publicly available diabetic retinopathy retinal fundus image datasets. For an unbiased assessment of performance, the dataset was divided into training and testing sets. Models were trained using deep learning frameworks based on Python, and their real-time viability was assessed using a Raspberry Pi 4. Modules for user interaction, lesion detection, and classification are all part of a Flask-based web interface.

### B. Classification Performance Analysis

For classification, deep feature extraction was performed using ResNet, GoogleNet, their hybrid combination, and the extended Xception model. Adaptive Particle Swarm

Optimization (APSO) was applied to select optimal features before classification. We evaluated Radial SVM, Random Forest, Decision Tree, Linear SVM, and Naive Bayes. In terms of accuracy and stability, the hybrid GoogleNet-ResNet and Xception-based models fared better than CNN models. The Voting Classifier (DT + RF) increased robustness by reducing misclassification across phases of diabetic retinopathy.

### C. Lesion Detection Performance

The lesion detection capability of the system was evaluated using multiple YOLO-based object detection models, namely YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n. These models were used to detect and localize retinal lesions such as microaneurysms, hemorrhages, and exudates. Experimental observations indicated that higher-capacity YOLO models achieved more precise lesion localization, while lightweight variants provided faster inference suitable for embedded systems. This demonstrates the effectiveness of YOLO models in lesion-centric diabetic retinopathy analysis.

### D. Embedded Deployment and Real-Time Evaluation

To assess real-time applicability, the optimized classification and detection models were deployed on a Raspberry Pi 4. The system achieved efficient inference with minimal latency, confirming its suitability for resource-constrained environments. The lightweight YOLO variants and optimized feature selection ensured reduced computational overhead without significant performance degradation. This validates the feasibility of deploying the proposed system in portable and rural healthcare settings.

### E. User Interface and System Usability

The Flask-based web interface was evaluated for usability and functionality. It provides secure user authentication, image upload, and real-time visualization of classification and lesion detection results. The interface enables easy interaction for healthcare professionals and supports rapid testing and screening. This integration improves accessibility and practical adoption of the proposed diabetic retinopathy detection system.

## EXPERIMENTAL RESULTS

The extended diabetic retinopathy detection system was evaluated to demonstrate the effectiveness of the Xception model, different machine learning classifiers, and YOLO-based lesion detection. Images of the retinal fundus were used for testing and training. Xception-

based feature extraction with traditional machine learning classifiers increased classification accuracy and stability when compared to CNN models. The inclusion of the Voting Classifier (Decision Tree + Random Forest) further enhanced robustness by reducing classification variance across different diabetic retinopathy stages. The application of Adaptive Particle Swarm Optimization (APSO) contributed to improved performance by selecting the most relevant lesion-related features and reducing redundant information.

For lesion localization, the extended framework evaluated multiple YOLO variants, including YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n, to analyze detection accuracy and inference efficiency. High-capacity YOLO models provided precise localization of retinal lesions, while lightweight versions achieved faster inference suitable for embedded deployment. The integration of a Flask-based user interface enabled seamless image upload, real-time prediction visualization, and secure user interaction. Real-time testing on Raspberry Pi 4 confirmed that the optimized detection and classification pipeline operates efficiently with acceptable latency. These results demonstrate that the extended system improves diagnostic accuracy, real-time performance, and usability, making it a practical and scalable solution for diabetic retinopathy screening in resource-constrained healthcare environments.

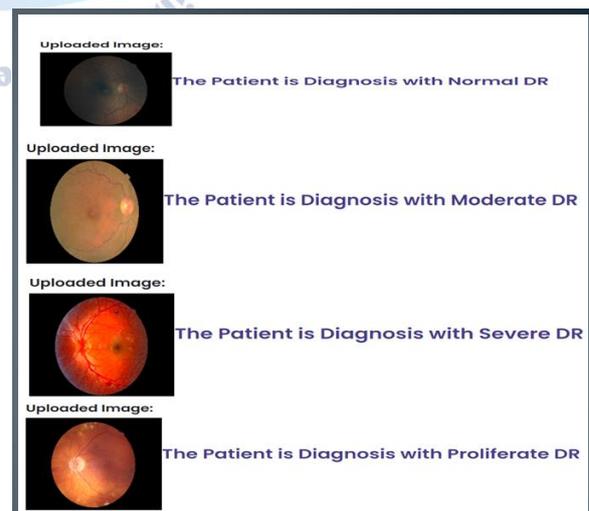


Fig4 Analysis results

## CONCLUSION

This work presented an extended lesion-centric diabetic retinopathy detection system that integrates hybrid deep learning, machine learning, and real-time object detection

techniques for accurate and efficient diagnosis. The proposed approach uses ensemble classification, adaptive particle swarm optimization, and feature extraction based on ResNet, GoogleNet, and Xception to consistently classify the stages of diabetic retinopathy. Retinal lesion localization is enhanced by several YOLO-based detection methods, which also increase clinical relevance and diagnostic interpretability. The Raspberry Pi 4 deployment and secure Flask-based web interface of the proposed framework show that it is appropriate for portable and real-time screening applications. The enhanced system balances accuracy, computational efficiency, and usability, making it suitable for remote and resource-constrained healthcare settings. The suggested early diabetic retinopathy screening approach is practical, affordable, and scalable, which enhances clinical judgment.

#### Future Scope

Multimodal retinal imaging data, such as OCT, can enhance the proposed diabetic retinopathy detection system. To improve early-stage diagnosis and disease progression analysis, future work may explore attention-based and transformer-driven architectures to enhance lesion-level feature representation and improve interpretability. The integration of explainable AI (XAI) techniques can provide visual and quantitative explanations for classification and lesion detection results, increasing clinical trust and adoption. Additionally, the system can be extended to support continuous learning and Federated learning frameworks make it possible for healthcare organizations to update their models without sharing patient data. Optimization for Raspberry Pi 5 and edge AI accelerators can further reduce inference latency and power consumption. Expanding the Flask-based platform into a cloud-assisted or mobile application with tele-ophthalmology support would enable large-scale deployment and remote diabetic retinopathy screening in rural and underserved regions.

#### Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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