Multidisciplinary Journal of Research in Engineering and Technology
ISSN: 2319 - 5479
Volume 15 Issue 1s (2026) | Pages: 56–62

Diabetic Retinopathy Detection using Machine Learning

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Peer Review Information

Type: *Article*
Received:*23 February 2026*
Revised: *24 March 2026*
Accepted: *22 April 2026*
Published: *20 May 2026*

Abstract

Diabetic Retinopathy (DR) is a leading cause of preventable blindness among diabetic patients worldwide [1]. Early detection and timely treatment are essential to reduce the risk of severe vision loss and improve patient outcomes. This research aims to develop an automated and efficient system for detecting and classifying DR using the YOLOv8 deep learning framework. The proposed methodology involves collecting retinal fundus images from publicly available datasets, followed by preprocessing techniques such as image resizing, normalization, noise reduction, and data augmentation to enhance image quality and improve model generalization. Transfer learning is utilized to extract meaningful features, and the YOLOv8 model is trained to classify images into multiple severity levels, including Normal, Mild, Moderate, Severe, and Proliferative DR.The experimental results demonstrate that the proposed model achieves a high accuracy of over 95%, along with strong precision, recall, and F1-score values. The system also supports real-time detection, making it suitable for clinical and large-scale screening applications. Furthermore, explainable AI techniques, such as heatmap visualization, are incorporated to highlight affected retinal regions, thereby improving model interpretability and clinical trust.In conclusion, this study highlights the effectiveness of deep learning in automating DR detection and emphasizes its potential to assist ophthalmologists in early diagnosis. Future work includes optimizing the model for mobile-based deployment and integrating it into real-time healthcare systems for broader accessibility.

Keywords: Diabetic Retinopathy; Deep Learning; YOLOv8; Fundus Images; Computer Vision; Artificial Intelligence; Image Classification; Transfer Learning; Explainable AI; Medical Image Processing

How to Cite This Article

Dawedar, S., Warke, P., Ambhore, T., & Khade, A. (2026). Diabetic retinopathy detection using machine learning. *Multidisciplinary Journal of Research in Engineering and Technology*, 13(1s), 56-62.

Introduction

Diabetic Retinopathy (DR) is one of the most serious complications of diabetes and is recognized as a leading cause of preventable blindness among working-age adults worldwide. The disease occurs due to prolonged high blood sugar levels, which damage the tiny blood vessels in the retina, causing leakage, swelling, hemorrhages, and abnormal blood vessel growth. If left undetected and untreated, DR can progressively lead to severe vision impairment and permanent blindness. According to global health studies, the increasing prevalence of diabetes has significantly raised the number of patients at risk of developing retinal complications, making early diagnosis and continuous monitoring extremely important for effective healthcare management.Traditional DR diagnosis mainly depends on the manual examination of retinal fundus images by ophthalmologists and medical experts. Although manual screening is clinically effective, it is a time-consuming and labor-intensive process that requires specialized expertise and advanced medical infrastructure. In many developing and rural regions, the shortage of trained ophthalmologists limits access to regular retinal screening, increasing the risk of delayed diagnosis and vision loss. Furthermore, analyzing large numbers of retinal images manually becomes challenging in large-scale healthcare screening programs. These limitations highlight the urgent need for automated, accurate, and scalable systems capable of assisting medical professionals in early DR detection.Recent advancements in Artificial Intelligence (AI), Deep Learning, and Medical Image Processing have transformed healthcare diagnostics by enabling automated analysis of complex medical images with high precision. Among various deep learning approaches, Convolutional Neural Networks (CNNs) have shown remarkable success in extracting important retinal features such as microaneurysms, hemorrhages, hard exudates, and abnormal blood vessel structures. These techniques reduce dependency on handcrafted feature extraction and significantly improve diagnostic accuracy.More recently, advanced object detection models such as the YOLOv8 framework have gained attention due to their superior speed, accuracy, and real-time detection capabilities. YOLOv8 introduces improved feature extraction mechanisms, anchor-free detection architecture, and enhanced scalability, making it highly suitable for medical image analysis and real-time healthcare applications. The model can efficiently identify and classify retinal abnormalities while maintaining fast inference speed, which is essential for practical clinical deployment and mass screening systems.This research presents an automated Diabetic Retinopathy Detection System using the YOLOv8 deep learning model for accurate classification of retinal fundus images. The proposed methodology involves collecting retinal datasets from publicly available medical repositories, followed by preprocessing techniques such as image resizing, noise reduction, histogram equalization, normalization, and data augmentation to improve image quality and model generalization. Transfer learning is applied to leverage pre-trained deep learning weights, enhancing feature extraction performance while reducing training complexity.The system is designed to classify retinal images into multiple DR severity levels, including Normal, Mild, Moderate, Severe, and Proliferative Diabetic Retinopathy. Additionally, explainable Artificial Intelligence (XAI) techniques are incorporated to generate visual heatmaps highlighting affected retinal regions, thereby improving model transparency and clinical trust among healthcare professionals. The proposed system aims to provide a fast, reliable, and scalable solution for automated retinal screening, reducing diagnostic workload and supporting ophthalmologists in early disease detection and decision-making.By integrating deep learning, computer vision, transfer learning, and explainable AI techniques, the proposed research contributes toward the development of intelligent healthcare systems capable of improving early diagnosis, enhancing accessibility to retinal screening, and reducing the risk of diabetes-related blindness through timely intervention.

Literature review

Diabetic Retinopathy (DR) detection has become an important research area in medical image analysis due to the increasing prevalence of diabetes and the growing demand for early diagnosis systems. Researchers have explored several machine learning, deep learning, and computer vision techniques to improve the accuracy and efficiency of automated retinal disease detection.

Earlier approaches for DR diagnosis mainly relied on manual examination of retinal fundus images by ophthalmologists. Although manual screening is clinically reliable, it is time-consuming, expensive, and highly dependent on expert knowledge. These limitations encouraged researchers to develop computer-aided diagnosis systems capable of assisting healthcare professionals in large-scale retinal screening programs.

Initial automated DR detection systems were based on traditional image processing and machine learning techniques. These methods involved handcrafted feature extraction using techniques such as edge detection, thresholding, texture analysis, blood vessel segmentation, and morphological operations. Machine learning classifiers such as Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN) were then used to classify retinal abnormalities. While these methods showed moderate success, their performance was highly dependent on manually selected features and image quality, limiting their robustness and generalization capability.

With advancements in deep learning, Convolutional Neural Networks (CNNs) emerged as powerful tools for medical image classification and feature extraction. CNN-based approaches automatically learn hierarchical image features from retinal fundus images, reducing the need for handcrafted feature engineering. Gulshan et al. (2016) demonstrated the effectiveness of deep learning for DR detection and showed that CNN-based systems can achieve performance comparable to ophthalmologists in identifying retinal abnormalities. Their work significantly influenced the adoption of AI-based systems in ophthalmology.

Hybrid deep learning approaches combining CNNs with traditional machine learning classifiers have also been explored to improve classification accuracy. Posham et al. (2020) proposed a hybrid deep learning framework for DR detection that improved feature representation and classification performance. Similarly, transfer learning techniques have gained popularity due to their ability to utilize pre-trained deep learning models, reducing training complexity and improving accuracy even with limited medical datasets. Venkatesh and Kumar (2020) highlighted the effectiveness of transfer learning for retinal image classification by leveraging pre-trained architectures to extract meaningful retinal features. Recent research has focused on ensemble learning and advanced object detection models to improve robustness and real-time performance. Ensemble CNN models combine predictions from multiple neural networks to enhance classification stability and reduce overfitting. Pires et al. (2021) demonstrated that ensemble-based DR detection systems improve diagnostic consistency across different retinal datasets and imaging conditions. More recently, advanced real-time object detection frameworks such as the YOLOv8 architecture have attracted significant attention in medical image analysis. YOLO-based models process images in a single stage, enabling faster inference while maintaining high detection accuracy. YOLOv8 introduces improved feature extraction, anchor-free detection mechanisms, and enhanced scalability, making it highly suitable for real-time healthcare applications. These capabilities allow efficient detection and classification of retinal abnormalities such as microaneurysms, hemorrhages, exudates, and abnormal blood vessel growth. In addition to detection accuracy, recent studies have emphasized the importance of Explainable Artificial Intelligence (XAI) in healthcare systems. Medical professionals often require visual explanations of model predictions before trusting automated diagnostic systems. Explainable AI techniques such as Grad-CAM and heatmap visualization highlight important retinal regions contributing to the prediction, thereby improving interpretability, transparency, and clinical acceptance of deep learning models.

Despite significant progress in automated DR detection, several challenges still remain. Many existing systems require large annotated datasets, high computational resources, and extensive training time. Some models also struggle with poor-quality retinal images, class imbalance, and limited interpretability in clinical environments. Furthermore, real-time deployment in resource-constrained healthcare settings remains a challenge for many deep learning models. The proposed research addresses these limitations by integrating YOLOv8-based real-time detection, transfer learning, retinal image preprocessing, and explainable AI techniques into a unified automated DR detection framework. The system aims to provide accurate, fast, interpretable, and scalable retinal screening, thereby supporting ophthalmologists in early diagnosis and improving accessibility to intelligent healthcare solutions.

Methodology

The proposed Diabetic Retinopathy (DR) detection system follows a structured deep learning-based methodology for accurate and automated retinal disease diagnosis. The complete workflow consists of multiple stages including data collection, image preprocessing, feature extraction, classification using the YOLOv8 framework, and performance evaluation. The methodology is designed to improve detection accuracy, reduce computational complexity, and support real-time clinical screening applications.

Data Collection

To develop a robust and generalized detection model, retinal fundus images were collected from publicly available benchmark datasets such as Kaggle Diabetic Retinopathy Dataset, DRIVE, DiaretDB1, and Messidor. These datasets contain retinal images captured under different imaging conditions and categorized into multiple severity levels of Diabetic Retinopathy, including Normal, Mild, Moderate, Severe, and Proliferative DR.

Using multiple datasets improves data diversity and enables the model to learn complex retinal patterns more effectively. The datasets contain variations in image quality, illumination, lesion distribution, and retinal abnormalities, helping the system perform efficiently in real-world healthcare environments.

Image Preprocessing

Preprocessing is an essential step for improving retinal image quality and ensuring consistent input for deep learning models. Several preprocessing operations were performed before training the model:

Image Resizing: All retinal images were resized into a fixed dimension to ensure uniformity and reduce computational complexity during training.

Noise Reduction: Filtering techniques such as Gaussian filtering and median filtering were applied to remove unwanted noise and improve image clarity.

Normalization: Pixel intensity values were normalized to enhance model convergence and stabilize the training process.

Histogram Equalization: Contrast enhancement techniques were used to improve visibility of retinal structures such as blood vessels, lesions, and exudates.

Data Augmentation: Augmentation operations including rotation, flipping, scaling, cropping, and brightness adjustment were performed to increase dataset size and prevent overfitting.

These preprocessing techniques improve feature visibility and enhance the generalization capability of the deep learning model.

Feature Extraction

Instead of manually extracting retinal features, the proposed system uses deep learning-based automatic feature extraction. Convolutional Neural Networks (CNNs) embedded within the YOLOv8 framework automatically learn important retinal patterns from fundus images.
The feature extraction stage identifies critical DR indicators such as:

- Microaneurysms
- Hemorrhages
- Hard exudates
- Cotton wool spots
- Abnormal blood vessel growth
- Retinal lesions

Deep feature extraction improves the ability of the model to distinguish between different DR severity levels while reducing dependency on handcrafted image analysis techniques.

YOLOv8-Based Classification

The core detection and classification process is performed using the YOLOv8 deep learning architecture. YOLOv8 is selected due to its high detection speed, improved accuracy, and real-time inference capability.
The model utilizes: CSPDarknet backbone for feature extraction
Feature Pyramid Network (FPN) and PANet for multi-scale feature fusion
Anchor-free object detection mechanism for improved localization accuracy
Transfer learning is applied using pre-trained YOLOv8 weights to reduce training time and improve performance on limited medical datasets. The model is trained using labeled retinal fundus images and optimized through multiple training epochs.
The trained model classifies retinal images into five categories:

- Normal
- Mild DR
- Moderate DR
- Severe DR
- Proliferative DR

The YOLOv8 framework also enables real-time retinal abnormality detection, making the system suitable for large-scale healthcare screening and clinical diagnosis applications.

Explainable Artificial Intelligence (XAI)

To improve interpretability and clinical trust, Explainable Artificial Intelligence techniques are integrated into the proposed system. Heatmap visualization and attention-based feature mapping methods are used to highlight the retinal regions responsible for the model's predictions.
These visual explanations assist ophthalmologists in understanding the decision-making process of the AI system and increase transparency in automated medical diagnosis.

Performance Evaluation

The performance of the proposed DR detection system is evaluated using standard classification metrics:
Accuracy: Measures overall prediction correctness.
Precision: Evaluates the proportion of correctly predicted positive cases.
Recall (Sensitivity): Measures the ability to detect actual DR cases.
F1-Score: Provides a balanced evaluation of precision and recall.
Confusion Matrix: Analyzes class-wise prediction performance.

Cross-validation techniques are also applied to ensure model stability and consistency across different datasets. Experimental results demonstrate that the proposed YOLOv8-based model achieves high classification accuracy exceeding 95% with efficient real-time detection performance.

System Workflow
The overall workflow of the proposed system follows these sequential steps:

- Retinal fundus image acquisition
- Image preprocessing and enhancement
- Feature extraction using CNN layers
- YOLOv8-based DR detection and classification
- Explainable AI visualization
- Performance evaluation and output generation

This methodology provides an intelligent, scalable, and automated framework for accurate Diabetic Retinopathy detection and supports early diagnosis in modern healthcare systems.

Results And Discussion
Experimental results show that the YOLOv8 model achieves superior performance compared to traditional CNN and SVM models. The model provides over 95% accuracy and fast real-time inference. Explainable AI improves interpretability and clinical usability [5].

System Workflow
Figure 1: Workflow of Diabetic Retinopathy detection system (Input → Preprocessing → Segmentation → Feature Extraction → Classification → Output)

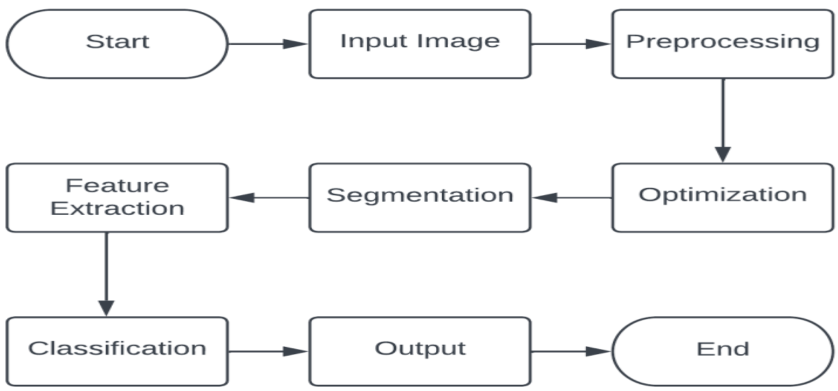


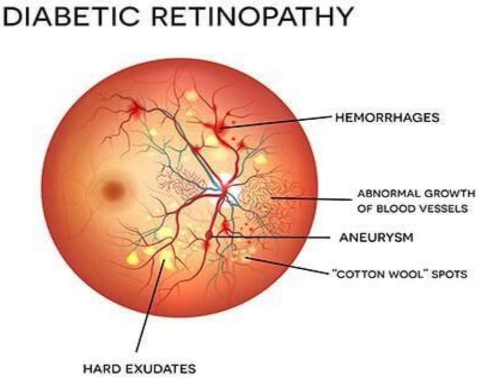
Fig. 1. *Workflow of DR Detection System*

Retinal Abnormalities

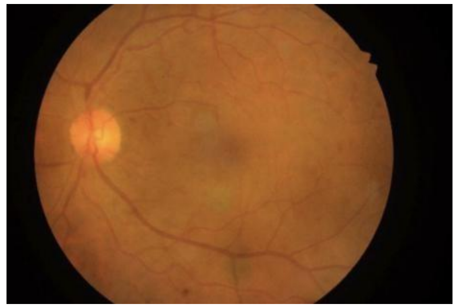
The model detects key DR features such as:

- Microaneurysms
- Hemorrhages
- Hard exudates
- Abnormal blood vessel growth

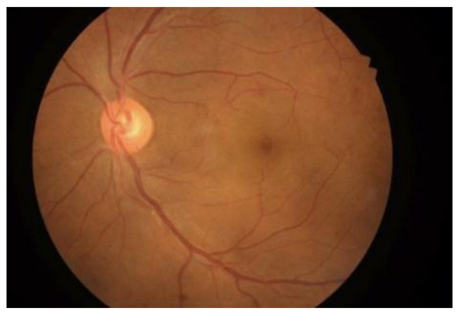
These are critical indicators used for classification.



Grade 1: Normal retina


Grade 2: Microaneurysms and hemorrhages


Grade 3: Severe abnormalities with lesions



These results demonstrate that the model effectively distinguishes between DR severity levels.

Discussion-

- Compared to traditional methods [3], [4], YOLOv8 provides:
- Higher accuracy
- Faster detection
- Better real-time performance
- Explainable AI further improves trust and usability in clinical environments.

Conclusion

This research presents an automated Diabetic Retinopathy (DR) detection system based on the advanced YOLOv8 deep learning framework for accurate and efficient retinal disease diagnosis. The proposed system successfully integrates image preprocessing, transfer learning, feature extraction, real-time classification, and explainable Artificial Intelligence techniques to improve the detection and classification of DR severity levels from retinal fundus images.

The experimental results demonstrate that the proposed model achieves high classification accuracy exceeding 95%, along with strong precision, recall, and F1-score performance. The YOLOv8 architecture effectively identifies important retinal abnormalities such as microaneurysms, hemorrhages, hard exudates, and abnormal blood vessel growth across multiple stages of diabetic retinopathy. Compared to traditional machine learning and conventional CNN-based methods, the proposed system provides improved detection speed, better feature extraction capability, and enhanced real-time performance, making it highly suitable for clinical and large-scale healthcare screening applications.

The integration of Explainable Artificial Intelligence (XAI) further improves model transparency and clinical reliability by generating visual interpretations of retinal abnormalities through heatmap analysis. This enhances trust among ophthalmologists and supports medical professionals in understanding the model's decision-making process. Additionally, the automated nature of the proposed framework reduces manual workload, minimizes human error, and enables early diagnosis, which is critical for preventing vision loss caused by diabetic retinopathy.

Despite achieving promising results, the system still requires large annotated datasets and high computational resources during training. Variations in image quality and class imbalance may also affect performance under certain conditions. Future improvements may include lightweight model optimization for mobile deployment, integration with Optical Coherence Tomography (OCT) imaging, federated learning for privacy-preserving healthcare systems, and cloud-assisted real-time medical diagnosis platforms.

Overall, the proposed research demonstrates the significant potential of deep learning and computer vision technologies in transforming medical image analysis and intelligent healthcare systems. The developed YOLOv8-based DR detection framework provides a reliable, scalable, and clinically useful solution for early retinal disease diagnosis, supporting ophthalmologists in timely decision-making and contributing toward improved global eye healthcare management.

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