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Review on Deep Vision for Early Detection of Diabetic Retinopathy using Machine Learning

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Abstract

Diabetic Retinopathy (DR) is one of the most severe microvascular complications of diabetes mellitus and a leading cause of preventable blindness worldwide. Early diagnosis and timely treatment are critical, as DR often progresses asymptomatically until irreversible retinal damage occurs. Conventional diagnosis relies on manual examination of retinal fundus images by ophthalmologists, which is time-consuming, costly, and subject to inter-observer variability. Recent advancements in computer-aided diagnosis have demonstrated that machine learning, particularly deep learning, can significantly enhance the accuracy and efficiency of DR detection. Convolutional Neural Networks (CNNs) have emerged as the most effective approach for automated analysis of fundus images due to their capability to learn hierarchical and discriminative features directly from raw data. This review presents a comprehensive analysis of recent deep learning–based methods for diabetic retinopathy detection, classification, and severity grading. Key aspects such as preprocessing techniques, network architectures, publicly available datasets, and evaluation metrics are discussed. Furthermore, existing challenges including dataset imbalance, lack of interpretability, and limited clinical deployment are highlighted. The review also identifies emerging trends and future research directions aimed at developing robust, explainable, and scalable DR screening systems suitable for real-world clinical applications.

Keywords: Diabetic Retinopathy (DR), Fundus Image, convolutional neural networks, Automated Disease Classification etc.

1. Introduction

Diabetes mellitus has become a major global health concern, with its prevalence increasing rapidly across both developed and developing countries. Among its various complications, diabetic retinopathy (DR) is one of the most serious and vision-threatening conditions, affecting the retinal microvasculature and leading to progressive visual impairment. According to clinical studies, nearly 80% of individuals who have had diabetes for more than 15–20 years develop some degree of DR, making it a leading cause of blindness among working-age adults worldwide [1], [2]. The major risk associated with DR lies in its asymptomatic nature during the early stages, which often delays diagnosis until irreversible retinal damage has already occurred.

Diabetic retinopathy is characterized by pathological changes such as microaneurysms, hemorrhages, hard exudates, cotton wool spots, and abnormal neovascularization. Clinically, the disease is categorized into two major stages: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR represents the early phase, marked by vascular leakage and retinal lesions, while PDR is the advanced stage characterized by the growth of fragile new blood vessels that may rupture and cause severe vision loss or retinal detachment [3]. Early identification of NPDR is crucial, as appropriate intervention at this stage can significantly reduce the risk of progression to PDR and blindness.

Traditionally, DR screening is performed through manual inspection of color fundus images by trained ophthalmologists. Although effective, this approach is limited by high screening costs, long examination times, and dependence on expert availability. Moreover, manual diagnosis is susceptible to fatigue-related errors and inter-observer variability, particularly in large-scale population screening programs [4]. These limitations are especially pronounced in rural and resource-constrained regions, where access to ophthalmic specialists is limited. As a result, there is a growing demand for automated, accurate, and scalable DR screening systems.

In response to these challenges, computer-aided diagnosis systems based on machine learning (ML) have been extensively explored. Early ML-based approaches relied on handcrafted feature extraction techniques combined with traditional classifiers such as Support Vector Machines and Random Forests. While these methods achieved moderate success, their performance was highly dependent on feature engineering and often lacked robustness when applied to large or diverse datasets [5]. Furthermore, these models struggled to generalize across variations in image quality, illumination, and patient demographics.

The emergence of deep learning (DL) has significantly transformed medical image analysis, including retinal image interpretation. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance in automatically learning discriminative features from raw fundus images without manual intervention [6], [7].

CNN-based systems have been successfully applied to DR detection, lesion segmentation, and severity grading, often achieving performance comparable to or exceeding that of human experts [8]. Publicly available datasets such as EyePACS, Messidor, and APTOS have further accelerated research by enabling standardized benchmarking of deep learning models.

Despite these advancements, several challenges remain. Many existing studies suffer from class imbalance, limited dataset diversity, and lack of external validation, which restricts real-world applicability [9]. Additionally, the "black-box" nature of deep learning models raises concerns regarding interpretability and clinical trust [10]. Recent research has therefore focused on explainable AI, lightweight architectures, and hybrid models to enhance transparency and deployability in real clinical environments [11],[13].

This review aims to systematically analyze recent deep learning–based approaches for diabetic retinopathy detection and grading. It highlights key methodologies, datasets, evaluation metrics, and performance trends reported in the literature. Furthermore, the review identifies open challenges and outlines future research directions toward developing reliable, interpretable, and scalable automated DR screening systems that can support ophthalmologists and improve early diagnosis, particularly in underserved regions [14], [15].

2. Problem Identification

Diabetic Retinopathy (DR) is a major complication of diabetes mellitus and a leading cause of preventable blindness worldwide. The primary challenge in managing DR lies in its asymptomatic progression during early stages, which delays diagnosis until significant retinal damage has occurred [1], [3]. Conventional screening relies on manual examination of retinal fundus images by ophthalmologists, a process that is time-consuming, expensive, and prone to inter-observer variability and human error, especially in large-scale screening programs [4]. In developing and rural regions, limited access to trained specialists further restricts timely diagnosis [2]. Traditional machine learning methods require handcrafted features and often fail to generalize well across diverse datasets and imaging conditions [5]. Although deep learning has shown promising performance, existing models still face challenges such as dataset imbalance, lack of interpretability, and limited clinical validation [9], [10]. These limitations highlight the need for robust, explainable, and scalable automated DR detection systems for early diagnosis.

3. Literature Survey

A) Literature Review

Tsiknakis et al. (2021), This comprehensive review explores how deep learning methods have transformed every stage of diabetic retinopathy analysis, from preprocessing and lesion segmentation to grading severity. The authors detail commonly used CNN architectures, benchmark datasets (e.g., Messidor, EyePACS), and performance gains from transfer learning. They also highlight limitations such as dataset imbalance, overfitting in smaller datasets, and the need for clinically validated models. The review concludes that DL models significantly outperform classical ML but stresses the importance of explainability and integration into real workflows.

Bhulakshmi et al. (2024), This review systematically surveys contemporary DL approaches for DR screening, focusing on classification and severity grading using retinal fundus images. It outlines key steps such as image preprocessing, feature extraction, and model evaluation strategies. The article highlights challenges like dataset quality variation, labeling inconsistencies, and computational costs of deep architectures. The authors emphasize growing trends in using ensemble learning and transfer learning to overcome generalizability obstacles and point toward hybrid models for real-world deployment.

Naz et al. (2024), review both supervised and unsupervised learning paradigms applied to DR detection, analyzing 103 research articles spanning large databases like Web of Science and Scopus. They comprehensively summarize how supervised CNNs excel at classification with labeled data, while unsupervised approaches help in feature learning without annotated datasets. They also discuss preprocessing, segmentation techniques, and comparison of model performance across studies. The authors call for standard benchmarks and hybrid strategies to improve generalizability in clinical scenarios.

Dejene et al. (2025), review assesses how ML and DL methods are applied to DR screening, comparing classical feature-based ML with modern CNN approaches. It highlights challenges such as lack of standardized fundus image datasets, high model complexity, and computational constraints for real-time deployment. The review underscores the effectiveness of DL models in lesion detection and severity grading, yet notes the necessity of explainability and hardware-efficient architectures for resource-limited settings. It suggests future research directions including federated learning for privacy and larger multiethnic datasets.

Nadeem et al. (2022), This review extensively analyzes the use of deep learning in DR detection, segmentation, and progression prediction. It outlines the integration of CNNs, transfer learning, and data augmentation techniques to overcome limited annotated data. The authors examine model robustness across multiple datasets and discuss challenges like feature interpretability. They also explore future trends such as self-supervised learning, cross-domain adaptation, and integrating clinical metadata with imaging features to boost diagnostic accuracy and reliability in diverse populations.

Muthusamy & Palani (2024), The authors review deep neural network models designed to classify DR severity using fundus images, detailing feature extraction layers and network optimization techniques. They assess how multi-layer perceptron architectures improve DR detection by learning complex representations of retinal abnormalities. The review discusses results from recent studies on benchmark datasets and emphasizes using data augmentation to enhance model performance. They also explore model explainability techniques, concluding that clear visualization of learned features enhances clinical trust and adoption.

Aghabeigi Alooghareh et. al. (2025), This review examines emerging deep learning strategies for retinal disease detection beyond DR, with strong implications for DR screening models. It highlights vision transformer architectures and gradient-based saliency maps for explainability, demonstrating how new models interpret key retinal features. The authors argue that interpretability and clinical applicability are as critical as raw accuracy, and propose frameworks integrating attention mechanisms for better lesion localization and severity grading. The paper suggests that multimodal learning, combining imaging and clinical data, could elevate diagnostic precision.

Alyoubi et al. (2020), review focuses on state-of-the-art DR detection and classification models using CNNs. It outlines fundamental steps like preprocessing, network design, dataset selection, and evaluation metrics. The authors compare model performance across popular fundus image datasets and discuss challenges such as image quality variations and class imbalance. They emphasize transfer learning and fine-tuning pretrained networks to achieve higher detection rates even with limited data. The review concludes that DL outperforms traditional methods but calls for robust clinical validations.

A. Gautam et. al. (2025), This review examines an array of DR detection techniques using deep learning frameworks, comparing methodologies, network architectures (like ResNet, VGG), and transfer learning approaches. Key challenges include inconsistent data labeling, variation in dataset quality, and the lack of unified evaluation protocols. The authors synthesize recent advances and highlight trends toward hybrid models that integrate deep learning with traditional ML classifiers for improved generalization in real-world screening.

L. Lestari et. al. (2025), This recent review covers nearly 128 research studies on automated DR diagnosis from fundus images extending from classical image processing to deep networks. The review details network design choices, preprocessing pipelines, and performance metrics across architectures. It emphasizes the evolution from simple CNN models to attention-based and hybrid ensembles, highlighting clinical pathway integration and prospects for tele-ophthalmology screening at scale. The authors also discuss open research issues like dataset standardization and real-time mobile applications.

N. U. Haq et. al. (2025), This review explores multimodal DL frameworks combining fundus images with additional clinical data for enhanced DR diagnosis. It highlights trends toward self-supervised learning, attention architectures, and hybrid models that address data scarcity and model interpretability. The authors discuss future directions in standardized multimodal datasets, explainable AI, and integrated diagnostic workflows for clinical decision support systems.

Lestari et. al. (2023), review examines the use of AI algorithms in real-world DR screening, especially in Asian populations, and compares diagnostic accuracy across studies. It finds that AI can reliably identify referable DR from large fundus image datasets without a retina specialist, with high sensitivity and specificity in most studies. The review recommends wider adoption in low-resource settings but highlights the need for robust data governance and algorithm validation across diverse populations.

NU Haq et. al. (2024), This survey builds upon earlier work by analyzing how optimized DL models balance accuracy and computational cost, making them suitable for mobile and edge devices. It discusses challenges like model scaling, pruning, and quantization to enable real-time inference. The authors argue that embracing efficient architectures (e.g., MobileNet, EfficientNet) can broaden DR screening access in remote regions while maintaining performance comparable to heavier networks.

A Zafar et. al. (2025), This review highlights recent DL innovations for DR detecting and grading with a focus on lightweight, interpretable models. It synthesizes multiple studies that use pretrained networks, transfer learning, and hybrid modules to improve detection accuracy while reducing model complexity. The authors stress the importance of visual explanations and clinician-friendly outputs for adoption in practice. Key future directions include self-supervised learning and standardized evaluation benchmarks.

A. Mary Dayana & W. R. Sam Emmanuel (2023), This extensive survey analyzes deep learning and metaheuristic optimization techniques to improve DR detection and severity grading from fundus images. It compares traditional CNNs, transfer learning models, and optimization-based feature selection strategies. The authors underscore the importance of preprocessing, class balancing, and ensemble approaches for robust and interpretable predictions. They highlight future research opportunities including federated learning, GAN-based augmentation, and real-world validation.

B) Literature Summary

Recent literature highlights significant advancements in automated diabetic retinopathy (DR) detection using machine learning and deep learning techniques. Early studies employed traditional machine learning classifiers with handcrafted features; however, their performance was limited by poor generalization and sensitivity to image quality variations [5]. With the emergence of deep learning, particularly convolutional neural networks (CNNs), researchers achieved substantial

improvements in accuracy, sensitivity, and robustness for DR classification and grading tasks [1], [6]. Transfer learning using pretrained models such as VGG, ResNet, and EfficientNet has been widely adopted to address limited labeled data and reduce training complexity [7], [11]. Public datasets like EyePACS and Messidor have enabled standardized evaluation and benchmarking of models [2], [8]. Despite these advances, challenges persist, including class imbalance, lack of explainable decision-making, and limited clinical deployment, motivating further research toward interpretable, scalable, and real-world-ready DR screening systems [9], [10].

C) Research Gap

• Most existing deep learning models for diabetic retinopathy (DR) detection are trained and evaluated on limited or single-source datasets, leading to poor generalization across diverse populations and imaging conditions.
• Class imbalance in publicly available retinal datasets remains inadequately addressed, often resulting in biased predictions toward majority classes.
• Many studies prioritize high accuracy while neglecting model interpretability, limiting clinical trust and acceptance among ophthalmologists.
• Real-time and resource-efficient implementations suitable for deployment in rural or low-resource healthcare settings are insufficiently explored.
• Limited integration of clinical metadata (patient history, duration of diabetes) with fundus image analysis restricts holistic diagnosis.
• Few works report large-scale clinical validation or long-term performance evaluation, creating a gap between research outcomes and real-world clinical adoption.

4. Research Methodology

A) Criteria for selecting this study:

• The study focuses on deep learning–based approaches for diabetic retinopathy (DR) detection, which represent the current state-of-the-art in automated retinal image analysis.
• Priority is given to recent peer-reviewed publications (2020–2025) to ensure technological relevance and updated methodologies.
• Studies utilizing publicly available and clinically recognized datasets (e.g., EyePACS, Messidor, APTOS) are selected to ensure reproducibility and benchmarking consistency.
• Research addressing early detection and severity grading of DR is emphasized due to its clinical importance in preventing vision loss.
• Works incorporating advanced preprocessing, data augmentation, or transfer learning techniques are included for improved robustness.
• Preference is given to studies reporting quantitative performance metrics such as accuracy, sensitivity, specificity, and AUC for objective evaluation.

B) Method of analysis:

• A systematic analysis of selected studies is conducted by categorizing them based on model architecture, including CNNs, hybrid models, and ensemble frameworks.
• Comparative evaluation is performed using reported performance metrics such as accuracy, precision, recall, sensitivity, specificity, and AUC.
• The role of image preprocessing and augmentation techniques in enhancing model performance is critically examined.
• Dataset characteristics, including size, class distribution, and image quality, are analyzed to assess their impact on

model generalization.

• Limitations and challenges identified by each study, such as overfitting or lack of explainability, are reviewed.

• Emerging trends and future research directions are synthesized to identify gaps and opportunities for further improvement.

C) Comparison and Analysis:

Table 1. Comparison and Analysis of Literature on Diabetic Retinopathy Detection.

Author(s) & Year	**Method / Model Used**	**Dataset Used**	**Key Findings / Performance**
Tsiknakis et al., 2021	CNN, Transfer Learning, Ensemble DL	EyePACS, Messidor	Achieved expert-level DR detection accuracy; highlighted need for explainability and clinical validation.
Alyoubi et al., 2020	Deep CNN architectures	Messidor, DRIVE	CNN-based models outperformed traditional ML; preprocessing significantly improved sensitivity.

Nadeem et al., 2022	CNN, Hybrid DL Models	EyePACS, APTOS	Demonstrated high robustness using transfer learning; data augmentation improved generalization.
Lestari, 2023	AI-based Screening Models	Regional clinical datasets	Reported high sensitivity and specificity; suitable for large-scale DR screening programs.
Bhulakshmi et al., 2024	CNN, Ensemble Learning	EyePACS, Kaggle DR	Ensemble DL models improved classification accuracy; class imbalance remained a challenge.
Naz et al., 2024	Supervised & Unsupervised DL	Multiple public datasets	Supervised CNNs performed better; unsupervised methods useful with limited annotations.
Haq et al., 2024	EfficientNet, MobileNet	APTOS, Messidor	Lightweight models achieved comparable accuracy with reduced computation cost.
Muthusamy & Palani, 2024	Deep Neural Networks	Kaggle DR Dataset	Improved severity grading accuracy; emphasized need for explainable AI.
Dejene, 2025	ML vs DL Comparison	Messidor, EyePACS	DL significantly outperformed classical ML; scalability issues noted.
Zafar et al., 2025	Lightweight Multi-DL Frameworks	Fundus image datasets	Balanced accuracy and computational efficiency; suitable for rural deployment

D) *Evaluation of methodologies used in the reviewed studies*

The methodologies adopted in the reviewed studies demonstrate a clear progression from traditional machine learning techniques to advanced deep learning frameworks for diabetic retinopathy (DR) detection. Most recent works rely on convolutional neural networks (CNNs) due to their superior capability in automatically learning hierarchical features from retinal fundus images. Transfer learning using pretrained models such as VGG, ResNet, and EfficientNet has been widely employed to address limited labeled data and reduce training time. Several studies incorporated data augmentation and image preprocessing to enhance robustness against variations in illumination and image quality. Ensemble and hybrid models further improved classification accuracy by combining multiple network outputs. However, many methodologies lack standardized evaluation protocols and external clinical validation. Additionally, limited attention has been given to explainable AI techniques, which restricts clinical interpretability. Overall, while deep learning methodologies show strong performance, further methodological refinement is required for real-world deployment.

E) Highlighting trends, advancements, and challenges

Trends:
• Increasing adoption of deep learning–based approaches, particularly convolutional neural networks (CNNs), for automated diabetic retinopathy (DR) detection.
• Widespread use of transfer learning with pretrained models such as ResNet, VGG, and EfficientNet to improve performance on limited datasets.
• Growing focus on early-stage DR detection and severity grading rather than binary classification.
• Use of public benchmark datasets for standardized evaluation and comparison.
• Rising interest in lightweight and mobile-compatible models for large-scale screening applications.

Advancements:
• Significant improvement in diagnostic accuracy, sensitivity, and AUC using deep convolutional neural networks.
• Integration of ensemble learning and hybrid architectures to enhance robustness and reliability.
• Adoption of advanced preprocessing and data augmentation techniques to handle image variability.
• Emergence of explainable AI methods to visualize lesion regions and improve clinical trust.
• Development of computationally efficient models suitable for deployment in resource-constrained environments.

Challenges:
• Persistent class imbalance in retinal image datasets affecting model generalization.
• Limited availability of diverse and well-annotated clinical datasets.
• Lack of interpretability and transparency in deep learning decision-making.
• Insufficient external clinical validation and real-world deployment studies.
• High computational requirements of deep models, restricting scalability in low-resource healthcare settings.

5. Discussion

A) Synthesis of findings from literature

The reviewed literature demonstrates that deep learning has significantly advanced automated diabetic retinopathy (DR) detection by enabling accurate feature extraction and robust classification from retinal fundus images. Convolutional neural networks consistently outperform traditional machine learning techniques, particularly in early-stage DR identification and

severity grading. Transfer learning and data augmentation have proven effective in mitigating limited labeled data and improving model generalization. Ensemble and lightweight architectures further enhance performance while addressing computational efficiency. However, despite high reported accuracies, many studies rely on constrained datasets and lack external clinical validation. Issues such as class imbalance, interpretability, and real-world deployment remain unresolved. Overall, the synthesis indicates that while deep learning-based DR systems are highly promising, future research must focus on explainable, scalable, and clinically validated solutions to enable widespread adoption in practical healthcare environments.

B) Methodology for future research directions

Most existing methods for diabetic retinopathy (DR) classification focus on identifying and analyzing exudate features. The process typically begins with image preprocessing, where contrast is enhanced and noise is minimized for better clarity. After this, the bright regions in the retinal image are segmented and isolated to highlight possible exudate areas. To find patterns that point to DR, the collection and selection of features are then done. Following their extraction, these traits are categorized into mild, moderate, severe, and normal DR phases. The typical methods for fluid detection throughout DR classification are shown in Figure 3.

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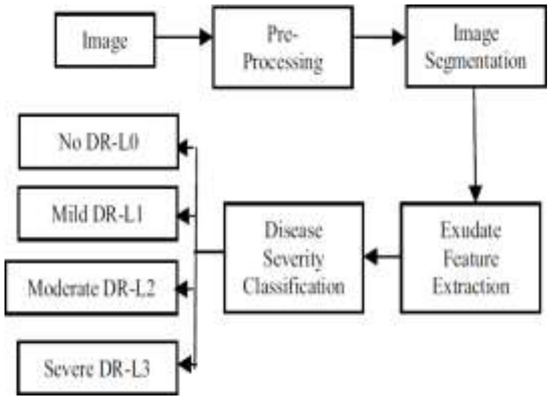

Fig. 3. Procedures for the DR Evaluation Application

The figure 3 illustrates the complete procedural workflow of a Diabetic Retinopathy (DR) Evaluation Application.

• The process begins with acquiring the retinal fundus image, which serves as the primary input for the system.

• The input image then undergoes pre-processing, where enhancement techniques such as contrast improvement, noise reduction, resizing, and illumination correction are applied to improve image clarity and diagnostic reliability.

• After preprocessing, the image is passed to the image segmentation stage, where important retinal structures and lesion regions are isolated. This segmentation helps in separating background regions and highlights clinical indicators such as exudates, hemorrhages, and microaneurysms.

• The segmented image is then processed in the exudate feature extraction block. Here, important disease-related features are extracted to analyze severity conditions accurately.

• The extracted features are transferred to the disease severity classification module, where the system categorizes the condition based on defined medical standards.

• Finally, the system classifies the retinal condition into four severity levels: No DR (L0), Mild DR (L1), Moderate DR (L2), and Severe DR (L3).

This structured flow ensures efficient early screening, accurate grading, and supports ophthalmologists in reliable automated DR assessment.

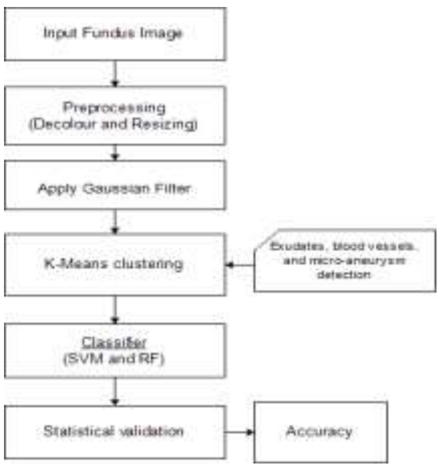

Fig. 4. Flow Chart

This flow chart represents the processing for Diabetic Retinopathy detection and classification using fundus images.

• The process begins with inputting the retinal fundus image, which is the primary source for disease diagnosis.

• The image undergoes preprocessing, where it is decolored, resized, and normalized to enhance quality and remove unwanted artifacts.

• A Gaussian filter is then applied to smooth the image and reduce noise, enabling clearer visualization of retinal structures.

• Next, K-means clustering is used for image segmentation to identify important retinal regions. During this step, the system detects exudates, blood vessels, and micro-aneurysms, which are key indicators of Diabetic Retinopathy.

• The extracted features are then passed to classification models, particularly Support Vector Machine (SVM) and Random Forest (RF), to classify disease severity or presence.
• Finally, the outcomes undergo statistical validation, where system accuracy and performance are evaluated to ensure reliability and effectiveness in medical diagnosis.

6. Conclusion

This review comprehensively examined recent advancements in machine learning and deep learning techniques for the early detection and grading of diabetic retinopathy (DR). The analysis highlights that convolutional neural networks have emerged as the most effective tools for automated retinal image analysis, offering superior accuracy and robustness compared to traditional feature-based machine learning approaches. Techniques such as transfer learning, data augmentation, ensemble modeling, and lightweight architectures have significantly improved model performance and computational efficiency, making large-scale screening increasingly feasible. Publicly available datasets have played a crucial role in benchmarking and accelerating research progress.
Despite these advancements, several challenges continue to limit real-world deployment. These include class imbalance in datasets, lack of model interpretability, insufficient diversity in training data, and limited clinical validation. Addressing these challenges is essential to bridge the gap between research prototypes and practical healthcare applications. Future work should prioritize explainable and trustworthy artificial intelligence, integration of clinical metadata, and extensive multi-center validation studies. Overall, deep learning–based automated DR screening systems hold substantial promise in supporting ophthalmologists, enabling early diagnosis, and reducing the global burden of diabetes-related blindness, particularly in resource-constrained and underserved regions.

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