Retina Grader – A Diabetic Retinopathy Classification System

Jacquelin Anushya P[1], Lavanya M[2], Gokul S[2], Hariharan N[3], Hariharan L[4] and Hari Prasanth A[5]
{anushyajacquelin21@gmail.com[1], Lavanyamarimuthu@gmail.com[2], gokul39164@gmail.com[3], hari98424haran@gmail.com[4], h205920@gmail.com[5], hariprasanth8608@gmail.com[6]}

Assistant Professor, Department of Computer Science and Engineering, SNS College of Technology, Coimbatore, Tamil Nadu, India[1, 2]
UG Students, Department of Computer Science and Engineering, SNS College of Technology, Coimbatore, Tamil Nadu, India[3, 4, 5]

Abstract. Diabetic Retinopathy (DR) is a serious complication of diabetes, being a major cause of blindness globally, necessitating early diagnosis for vision loss prevention. Conventional diagnostic approaches that utilize human examination of retinal fundus images are labor-intensive, error-prone and un- available in resource- limited regions. This study presents an AI- based approach using the deep learning ResNet-50 architecture to automate the detection and the classification of DR into five levels: Normal, Mild, Moderate, Severe, or Proliferative. Based on the Kaggle Diabetic Retinopathy Dataset, the system is equipped with data preprocessing including resizing, normalization, and augmentation to enhance the quality and balance of the data. ResNet-50 provides stronger feature extraction and classification to improve accuracy and reduce computation, collusion effects. An easy-to-use interface permits easy image upload, prediction and result visualization, and deployment in the cloud as well as offline makes it accessible. Such a system will contribute directly to global eye health by filling a gap in traditional diagnostics as a scalable, robust solution: preventing unnecessary blindness and disability.

Keywords: CNN, Resnet-50, DR, XAI, CAD, AI, ML.

1 Introduction

Diabetic Retinopathy (DR) is a leading cause of blindness around the world, which seriously reduces the quality of life of millions of people, especially those diagnosed with diabetes. It is a progressive disease that can cause damage to the retina the light-sensitive tissue at the back of the eye from long-term high blood sugar levels. Diabetic Retinopathy If not diagnosed and treated, diabetic retinopathy can cause permanent vision loss, or blindness. Diabetes is a growing problem worldwide with increasing urbanisation, sedentary lives, unhealthy diets and senior populations. Consequently, diabetic retinopathy has emerged as an increasing concern. Approximately one-third of people with diabetes will have some degree of diabetic retinopathy, and the risk increases with the duration and type of diabetes. Swift action to address the condition is critical to avoid its advancement into more serious stages. However, there are several challenges that hinder this requirement such as diabetic retinopathy being asymptomatic at an early stage. Meanwhile, many patients have no symptoms, like blurred vision or floaters, until the disease has already reached the moderate- or severe-stage and substantial damage may already be done. Early diagnosis and intervention are essential as the disease is potentially reversible. However, the classical diagnostic approaches, that predominantly depend on direct examination by ophthalmologists, are time consuming,

ICITSM-Part II 2025, April 28-29, Tiruchengode, India

DOI 10.4108/eai.28-4-2025.2358113

resource demanding, and anatomically error-prone, especially for dealing with mass populations. This situation requires integrating advanced technological tools to improve the accuracy, efficiency, and convenience of diabetic retinopathy screening. Recent innovations in Artificial Intelligence (AI) and Machine Learning (ML) have been making inroads in the area of medical diagnostics. Generative AI in particular has great potential for automating complicated tasks, analyzing big data, and making accurate predictions. Motivated by these progresses, we implemented "Retina Grader", a state-of-the-art system which can identify and classify the degree of diabetic retinopathy accurately. The app was trained on 3,000 retinal images which were carefully selected depicting a full spectrum of disease stages, including mild, moderate, severe, and extreme disease. Trained on this varied dataset, the system was able to classify diabetic retinopathy into five levels: No dr, Mid dr, Moderate dr, Severe dr, and Profilerate dr. This project uses Convolutional Neural Networks (CNNs) and Resnet 50 two of the most powerful AI models to examine retina images and offer diagnostic results based on six levels: Early; Normal; Mid; Moderate; High; and Extreme. Using Generative AI as a tool, Retina Gradaims to connect the world of clinical expertise with technology, presenting a powerful tool to both the clinicians and patients.

2 Literature Review

In recent years, detection and grading of diabetic retinopathy (DR) has received a lot of attention due to its being a global problem on the rise and the need for early diagnosis. Several deep learning techniques have been proposed for enhancing the performance, effectiveness and generalization of the automated DR screening systems. The important progress in this respect is described by refs. DenseNet pretrained in ImageNet was employed for automated DR grading (Akram et al., 2016). This work is a proof to the fact that dense block can re-use features by reducing number of parameters. However, it is not tested well on out-of-distribution samples and generalization might be worrisome. On the other hand, Retina Grader alleviates this problem with use of Densenet-based hybrid ensemble, and GANs for data augmentation that leads to improved robustness of model to practical clinical application cases. CNNs have also been utilized for handling the retinal blood vessel segmentation (in addition to obtaining accurate results during DR classification) (Alvarado-Carrillo et al., 2024). The models that use attention mechanisms can be almost perfectly accurate and interpretable – until they're not (Bhati et al., 2024). Retina Grader resolved this problem by implementing domain adaptation methods and diversifying its dataset. CNN also suggested developing an attention mechanism of the emphasis on retinal lesions which resulted in a remarkable improvement of classification accuracy (Al-Antary and Arafa, 2021; Xu et al., 2024). However, the domain shift between cross-dataset is also a critical issue. Retina Grader overcomes this limitation by using standard preprocessing and augmenting training data with synthetic images, in turn achieving a more generalizable model on a bigger scale.

ResNet50 and EfficientNet have been compared for DR classification, where EfficientNet has earned a better accuracy due to its better scalling strategy (Arora et al., 2024). But the compromises between model size and latency have yet to be explicitly managed. Retina Grader attempts to overcome these issues by employing small models that can operate in low-resource environments and ensemble learning to enhance robustness (Arora et al., 2024). Weighted combined strategies of deep neural networks have also been reported for early DR screening (Zhu et al., 2024). While this method shows the advantages of ensembling models, issues like imbalanced classes and interpretability are not addressed. Retina Grader addresses it with weighted loss and synthetic sample generation of minority data. Furthermore, SHAP has high interpretability of model that is beneficial for clinical decision-support systems. A hierarchical deep learning for fundus images has also been suggested for severity categorization (Senapati et al., 2024). Nevertheless, it does not consider class imbalance, leading to low sensitivity within early stage detection of the DR. This is addressed in Retina Grader architecture by adopting higher level classification models like ensemble of VGG16 and EffiientNet which compromised between computational efficiency and classification metrics (Kavitha, 2025).

Transfer learning-based VGG16 has also been used for DR classification, as providing high sensitivity for early detection (Alvarado-Carrillo et al., 2024). Deletion of a fixed single pattern however may lead to overfitting and suboptimal computational complexity. Retina Grader further improves this strategy by combining dropout regularization and data augmentation, as well as using ensemble models to attain cost-effectiveness in addition to accuracy (Thanikachalam et al., 2024; Rezaee et al., 2025).

The accurate segmentation of the retinal blood vessels for the classification of DR, especially on annotation datasets with a small number of samples, has also been an emphasis (Quellec et al., 2017; Z. Ai et al., 2021). This approach is intuitive, but the quality of the segmentation depends heavily on the quality of the model to begin with and creating such a high-quality model from scratch can be time consuming. Retina Grader improves upon this by fine-tuning pre-trained non-specific models and using data augmentation with synthetic data for better=performance in DR diagnosis (Akhtar et al., 2025).

3 Existing System

Diabetic Retinopathy (DR) is one of the major causes of visual loss and blindness world-wide, that demands an early detection to avoid serious consequences. The current diagnostic framework largely depends on hand-crafted manual assessment of retinal fundus images by ophthalmologists. Within this classical paradigm, physicians carefully analyze images searching for any anomalies such as microaneurysms, haemorrhagic signs and neovascularization, which are indicative of the development of DR. Although this is considered as a standard approach in many clinics there are significant limitations to this method. Manual inspection is inherently resource demanding, for which the availability of experts is limited, as a result, nose samples of people who can be effectively screened are greatly reduced. The diagnostic results with manual integration are variable and subjective. Signs of early-stage DR are subtle changes in retinal blood vessels, and can easily be missed even by experts. This heterogeneity is even worse in rural areas where access to ophthalmologists is poor and patients may have to wait for months to receive a diagnosis. Because of the potential for delayed or missed diagnoses, especially in early DR, which can lead to rapid progression and irreversible vision loss, there is an urgent need for accessibility in diabetic eye care.

4 Proposed System

This proposed system utilises state-of-the-art deep learning techniques with emphasis on the Resnet 50 model downloaded from MatConvNet, to overcome the deficiencies of current Diabetic Retinopathy (DR) detection methods. Conventional diagnostic systems which are based on manual assessment or simple machine-learning techniques may not be scalable, accurate or robust. The inclusion of a Resnet 50 architecture, a state-of-the-art neural network, allows the system to identify all the five stages of DR (Normal, Mild, Moderate, Severe, and PDR) with great precision. The approach ensures that the solution does not just work as a technical piece of excellence, but as a practical diagnostic solution. Fig 1 shows the proposed block diagram.

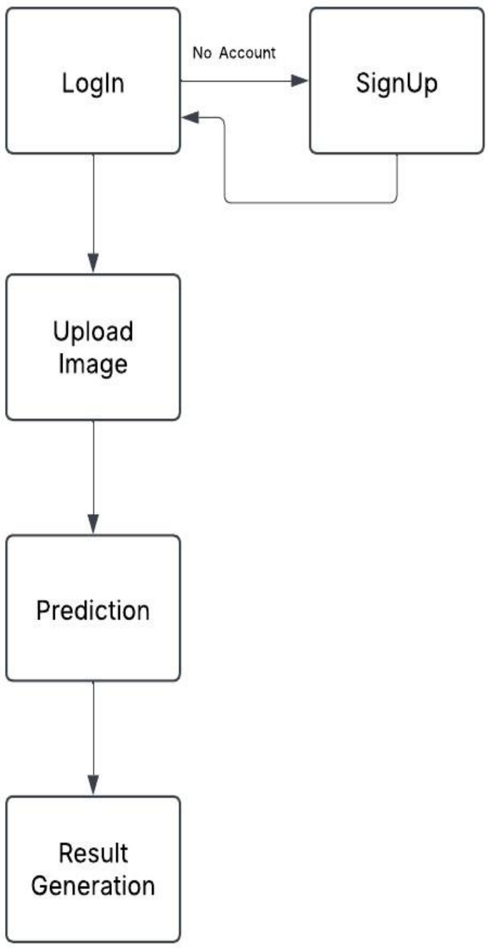

Fig. 1. Proposed Block Diagram.

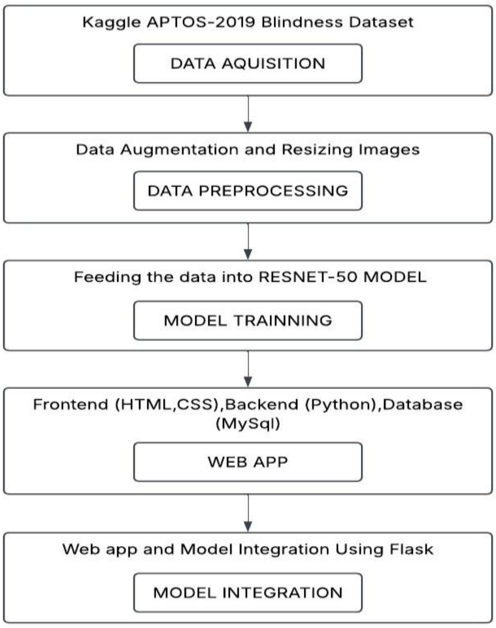

Fig.2. Layered approach.

The scalability is taken as a key aspect in the design of the proposed system. It is deployable on cloud-based and on-premises systems to meet the needs of a range of healthcare contexts. Cloud deployment allows for accessibility of the large-scale screening program even in the remote clinics and the underserved areas for the advanced diagnostics. On the other hand, local deployments options are designed to work offline and for regions with scarce internet connectivity and computational resources. This flexibility allows for adaptation of the system to specific requirements of various healthcare environments. The ability of the system to be deployed offline proves to be transformative in regions where access to diagnosis is limited. An adaptable and standalone solution, it also closes the Loop of Care delivery between urban center and rural patient population so that even the most underserved get access to early DR detection. This is consistent with the objectives of the international health agenda seeking to decrease healthcare disparities and to improve health outcomes in marginalised populations. Fig 2 shows the layered approach.

4.1 Data Collection and Preprocessing

The Data Collection and Preprocessing Module has an important role in the training of a good diabetic retinopathy detection model, as it provides the ResNet-50 architecture with high-quality input. Raw images are preprocessed (Pre-processing the raw images) using images from the APTOS 2019 Blindness Detection dataset containing about 3000 retinal fundus images and labeled with five DR stages. All the images resized are performed in a way that can be used by ResNet-50 and normalized consistently but further improved through noise reduction and applying different contrast methods, such as histogram equalization. Data augmentation such as flipping, cropping, and rotation are utilized to enrich the dataset for better generalization. Fig 3 shows the dataset visualization.

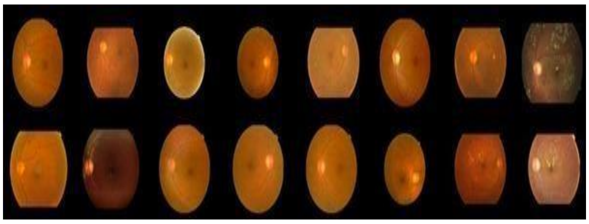

Fig. 3. Dataset Visualization.

To consider class imbalance, oversampling and synthetic data generation methods such as SMOTE and GANs maintain the balanced distribution of all DR stages. 70% of the dataset is used for training, 15% for validation, and 15% for testing to ensure the model is well-trained without being biased. Such pre-processing increases model accuracy and confidence in the detection of DR in vast clinical circumstances.

4.2 Model Training

The object of this module is to primarily develop, fine-tune and optimize the core detection model of the whole diabetic retinopathy stages classification from retinal images so that the best model architecture is selected and used ultimately.

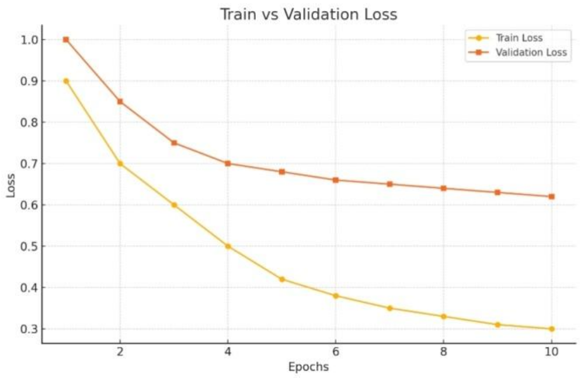

Fig. 4. Train Validation Loss.

Figure 4 shows the training process and generalization is improved by using transfer learning with pre-trained ImageNet weights, which enables the model to take advantage of learned features including edges, textures, and shapes. With our model based on the ResNet-50 architecture as the backbone, which is very scalable and computationally efficient for high-resolution images, the model takes the advantage of the capacity and generalization of high accuracy and low parameter count. During finetuning all layers that have already been pretrained are frozen and further layers are then treated to specialize at identifying DR specific parameters. In addition, our selective finetuning for some layers allows the model to adapt to the dataset-specific nature. To improve accuracy, techniques such as Adam optimizer and categorical cross-entropy loss function finetuning are used for training the model for increasing accuracy. Regularization techniques such as dropout and batch normalization additionally restrict overfitting, resulting in improved generalization to unseen samples. The training and validation scheme is strictly organized to guarantee the model's robust performance in clinical practice by dealing with the well-known issues of the overfitting and underfitting. The compound scaling method in ResNet-50, which equally modifies the depth, width, and resolution of the model, allows the model to find the tradeoff between accuracy and efficiency so that it can fit into the computational budgets. The model aims to detect subtle retinal features associated with both the existence and the severity of the diabetic retinopathy through the state-of-the-art feature-extraction processing.

4.3 Software Development

The Software serves as an important facet of the diabetic retinopathy detection system, whose goal is to afford clinicians in the healthcare domain an intuitive interface with which to interact with the model. We develop the UI to be workflow-efficient in the clinical integrated Applications, permitting the users to straightforward upload retinal images and view the model's predictions, as well as interpret the results. Based on Flask as backend framework, the UI keeps the server-side operation in a fluent state of receiving uploads, processing requests, and communicating with deep learning model. MySQL has been used for storing user account, image processing history and feedback from medical staff so as to maintain system continuity. The front end of the diabetic retinopathy detection system is implemented with HTML, CSS, and JavaScript, ensuring the interface is uncluttered, responsive, and user-friendly. HTML creates the structure of web pages.CSS adds visual appeal. JavaScript makes the web interactive. The users can upload high-resolution fundus images in the formats of JPG, PNG, and TIFF, which will be processed by a deep learning model constructed in PyTorch. Fig 5 shows the image upload page.

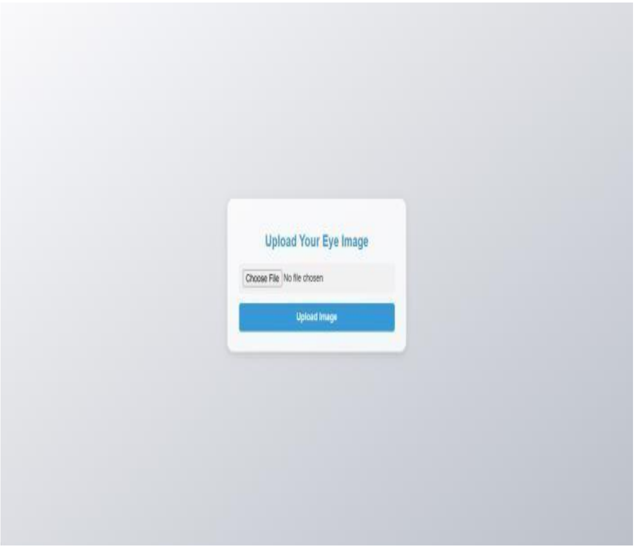

Fig. 5. Image Upload Page.

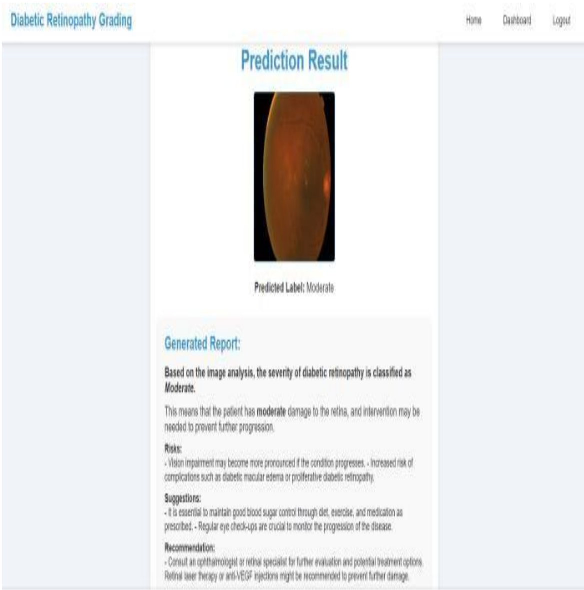

Fig. 6. Result Generation.

Fig 6 shows the result generation. The Flask backend refers to the mediator between the UI and the model, which preprocesses the image and passes it to the trained ResNet-50 model for prediction. After the model predicts the diabetic retinopathy stage (Normal, Mild, Moderate, Severe, Proliferative), Flask returns the predictions, updating the UI with the predicted label, and the confidence percentage which is also displayed using either progress bars or percentage labels. Results are categorized with a color coded scheme in the user interface (UI) to ensure fast decision making and a feedback module enables health care providers to confirm or correct predictions with this information being stored in MySQL, providing continuous model updating. Authentication for the secure access to the patient's data will prevent unauthorized access to the user's patient data, which results in the confidentiality and integrity. Using Flask to handling communication between the PyTorch model and the UI, and MySQL to store

4.4 Inference and Result Generation

The trained ResNet-50 is used for fetching the features from retinal images, inferring it, and generating the result which detects the diabetic retinopathy (DR) with high accuracy. The input images are pre-processed and submitted to a model that extracts the relevance features to classify the DR stage, Normal, Mild, Moderate, Severe and Proliferative, and their associated probability scores. These confidence scores inform clinical decisions, with greater probabilities indicating higher confidence in the predictions. For better interpretability, methods like GradCAM offer visual explanations which could support clinicians to justify predictions. This module will enable early identification, aid clinical decision-making, and help the seamless integration of AI into healthcare workflow thus producing better patient outcomes. Fig 7 shows the model accuracy graph.

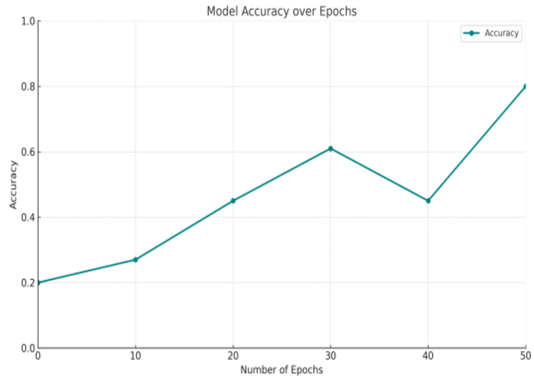

Fig.7. Model Accuracy Graph.

5 Results and Discussion

The Retina Grader project is a step towards facilitation of automated grading of Diabetic Retinopathy (DR) which employs a deep learning architecture for automated classification and aims at achieving improved accuracy, reduced expenditure as well as simplification of screening for the healthcare service providers. Utilizing the Kaggle's Diabetic Retinopathy Data dataset, the model is trained to differentiate fundus images for various DR levels with an aim to accurately detect abnormalities, such as microaneurysms, hemorrhages, and exudates. The prototype system built within Flask web app brings an end to end system closer to expected platform where users can log in and upload retinal images which get retinal image clinical features generated from Gen AI-created retval model.

DR grade reports instantly. All the predictions and their associated severities are organized in MySQL database and can be used to keep track of the prediction history. The web application is not only easy to use, but visually pleasing with a simple, dark navy and light blue, user friendly interface, which provides professional and intuitive environment. Through automated DR grading, the Retina Grader project reduces the burden of work for ophthalmologists, enables earlier detection in remote, less-resourced areas, and allows for the consistent, objective grading that is key to saving sight from DR.

6 Conclusion and Future Work

6.1 Conclusion

The Retina Grader is a deep learning-based DR automated detection system, which is expected to solve the problems such as resource shortage and expensive screening. The CNN is tuned with a labeled retinal fundus image dataset to classify DR grades and is an embedded into a Flask web app and backed by a MySQL database to store the results. An easy interface with dark navy and soft blue theme combination that will give the user, ease and comfort while using it and on the other hand received information will be more transparent due to performance metrics like confusion matrices and heatmaps. The system relieves ophthalmologist from excessive burden and also enhances the availability of sight-saving screening tests, especially in the underserved areas, by allowing early and inexpensive diagnosis of DR.

6.2 Future Work

Work that has to be done for the Retina Grader project includes increased accuracy and usability for the real world. Feature extraction and classification accuracy can be improved by incorporating stronger architectures such as ViTs or hybrid CNNRNN models into the deep learning model. Further enriching the data set with multi-ethnic, multivendor retinal images can enhance the robustness of the model, and more advanced AI interpretability techniques such as SHAP or LIME would provide better interpretability to clinicians. Implementing the system in a mobile app or edge device can support real-time, off-line screenings in remote villages. For one, Integration with telemedicine systems would allow remote diagnosis to be carried out, and federated learning would improve data privacy to ensure compliance with HIPAA and GDPR. Additionally, the platform can include an AI-based referral system, which uses AI to identify urgent cases, that interfaces with EHRs for managing patients with ease. Extending the model to identify other retinal diseases such as glaucoma, age related macular degeneration (AMD) and hypertensive retinopathy will have a more extensive clinical implication. Furthermore, integrating self-learning methods would enable the model to keep learning from the real feedback of clinicians, such as ophthalmologists. Once clinical trials are conducted and regulatory approval (FDA, CE etc.,) are met, then it will be proven effective to be used for real life application. These innovations will transform Retina Grader into a scalable, real-time, and clinically-validated AI tool and will increase access and decrease blindness in the world.

6.3 Final Remarks

In summary, the Retina Grader project demonstrated an integration of deep learning, medical image analysis and web technology to deliver a precise and universally accessible solution for diabetic retinopathy grading. By replacing the inefficient manual screening with robotic screening, the tool lightens ophthalmologists' workload, leading to earlier detection and better patient outcomes. The system’s scalability, explainability, and utility make it an effective tool for real-world clinical utility, particularly in resource-poor regions. As the models improve in accuracy, mobile incorporation and the implementation of AI-based diagnostics, Retina Grader has the potential to up-end retinal disease detection and improve global eye health.

References

[1] G. Quellec, K. Charrie, Y. Boudi, B. Cochener and M. Lamard, "Deep image mining for diabetic retinopathy screening," Med. Image Anal., vol. 39, pp. 178–193, 2017. DOI: 10.1016/j.media.2017.04.012.

[2] A. Bhati, N. Gour, P. Khanna, A. Ojha, and N. Werghi, “An interpretable dual attention network for diabetic retinopathy grading: IDANet,” Artif. Intell. Med. vol. 149, p. 102782, Mar. 2024. doi: 10.1016/j.artmed.2024.102782

[3] Z. Ai, X. Huang, Y. Fan, J. Feng, F. Zeng, and Y. Lu, “DR-IIXRN: Detection Algorithm of Diabetic Retinopathy Based on Deep Ensemble Learning and Attention Mechanism,” Front. Neuroinform., vol. 15, 2021. doi: 10.3389/fninf.2021.778552

[4] M. T. Al-Antary and Y. Arafa, “Multi-scale Attention Network for Diabetic Retinopathy Classification,” IEEE Access, vol. 9, pp. 3070685, 2021. doi: 10.1109/ACCESS.2021.3070685

[5] S. Akhtar, S. Aftab, O. Ali, M. Ahmad, M. Adnan Khan, Sagheer Abbas, Taher M. Ghazal et al., “A deep learning based model for diabetic retinopathy grading,” Scientific Reports, vol. 15, Art. no. 3763, 2025. doi: 10.1038/s41598-025-87171-9

[6] C. Xu et al., “An attentional mechanism model for segmenting multiple retinal lesions with enhanced diabetic retinopathy detection,” Sci. Rep. 2024. doi: 10.1038/s41598-024-72481-1

[7] Alvarado-Carrillo, D.E., Ovalle-Magallanes, E., Dalmau-Cedeño, O.S. (2024). LCAM-Net: Local Context Attention Network for Diabetic Retinopathy Severity Classification. In: Mezura-Montes, E., Acosta-Mesa, H.G., Carrasco-Ochoa, J.A., Martínez-Trinidad, J.F., Olvera-López, J.A. (eds) Pattern Recognition. MCPR 2024. Lecture Notes in Computer Science, vol 14755. Springer, Cham. https://doi.org/10.1007/978-3-031-62836-8_33

[8] L. Arora, S. K. Singh, S. Kumar, H. Gupta, W. Alhalabi, V. Arya, S. Bansal, K. T. Chui, B. B. Gupta et al., “Ensemble Deep Learning and EfficientNet for Accurate Diagnosis of Diabetic Retinopathy,” Scientific Reports, vol. 14, Art. no. 30554, 2024. doi: 10.1038/s41598-024-81132-4

[9] M. Akram, T. Dullo, R. Kim, L. Wang, A. Murugan, H. Gong, and Z. Zeng, “Uncertainty-aware Diabetic Retinopathy Detection using Bayesian DenseNet-121,” Scientific Reports, 2025. doi: 10.1038/s41598-024-84478-x

[10] V. Thanikachalam, P. Raju, and B. Sathish, “Optimized Deep CNN for Detection and Classification of Diabetic Retinopathy and Macular Edema Risk: A Cascaded Approach,” BMC Medical Imaging, vol. 24, Art. no. 406, 2024. doi: 10.1186/s12880-024-01406-1

[11] J. Xue, J. Xu, C. Weng, “Classification of Diabetic Retinopathy Based on Efficient Transformer-Based Models (VMamba-m),” Applied Sciences, vol. 14, no. 23, Art. no. 11327, 2024. doi: 10.3390/app142311327

[12] S. Zhu, C. Xiong, Q. Zhong, Y. Yao, “Diabetic Retinopathy Classification with Deep Learning via Fundus Images: A Short Survey,” IEEE Access, pp. 1-1, 2024. doi: 10.1109/ACCESS.2024.3361944.

[13] A. Senapati, P. S. Jambura, S. V. Jawahar, “Artificial Intelligence for Diabetic Retinopathy Detection: Transfer Learning based Methods,” Computers in Biology and Medicine, 2024. https://doi.org/10.1016/j.imu.2024.101445

[14] Kavitha, N.S., Kasthuri, N. An efficient automatic diabetic retinopathy grading using a two-way cascaded convolution neural network. *Discov Computing* **28**, 7 (2025). https://doi.org/10.1007/s10791-024-09486-x

[15] K. Rezaee, A. Shirmohammadi, M. Rezazadegan Tavakoli, “Innovative Approach for Diabetic Retinopathy Severity Classification using CNN-Transformer Hybrid,” 2025. doi: 10.31661/jbpe.v0i0.2408-1811