IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 3, March 2025

DOI: 10.17148/IJARCCE.2025.14342

A Review of Diabetic Retinopathy Disease Prediction using Deep Learning Techniques

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Abstract: Diabetic retinopathy is a severe eye disease that is fast spreading all over the world. It arises when blood sugar levels rise, leading to problems with the kidneys, eyes, and heart. Diabetic Retinopathy (DR) is an eye disease that is caused by the breakdown of blood vessels in the retina, which occurs as diabetes progresses. It is thought to be the main cause of visual impairment because it progresses asymptomatically at the early phases. This review article discusses the methods adopted in diabetic retinopathy detection, segmentation, and classification using deep and machine learning algorithms, and discusses their importance and limitations, along with potential future directions to overcome these limitations.

Keywords: Diabetic Retinopathy, Deep Learning, CNN, Accuracy.

I. INTRODUCTION

Diabetic retinopathy is a serious complication of diabetes-related vascular disease that can lead to vision loss and eventual blindness [1]. A break in the blood vessel of the retina is known as diabetic retinopathy (DR), which has a significant effect on certain age groups worldwide. Diabetic retinopathy often begins asymptomatically in early stages of vision loss; with the progression of the disease, symptoms become more evident [2]. Early detection of diseases improves treatment effectiveness and prevents the risk of negative outcomes.

The risk of vision loss is greatly reduced if diabetic retinopathy is detected and treated early. Diabetic retinopathy can now be detected non-invasively in its early stages with the advent of color fundus imaging. Diabetic retinopathy (DR) exists in two clinical stages: (1) non-proliferative diabetic retinopathy (NPDR) and (2) proliferative diabetic retinopathy (PDR) as shown in Fig. 1. Diabetic fundus disease begins with non-proliferative diabetic retinopathy (NPDR). Blood vessels in NPDR become permeable, leading to retinal edema. The most common reason for fuzzy vision and, in some cases, visual handicap is this. PDR, or proliferative diabetic retinopathy, is the second phase of degeneration of diabetic fundus. The development of too many blood vessels in the cornea causes this disease. Neovascularization is the term given to this procedure [3]. The patient can see a number of blurry floaters after having minimal bleeding. If they have major bleeding, they can lose their vision completely.

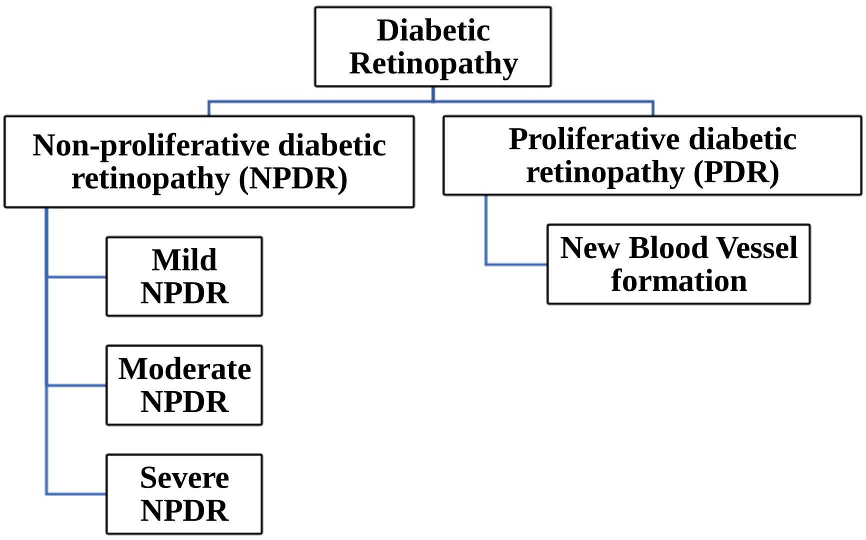

Fig. 1. Types of DR

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II. LITERATURE REVIEW

TABLE I REVIEW OF EXISTING METHODS

REF.	Dataset Used	Methodology used	Results
[4]	• The study utilized the Ocular Disease Intelligent Recognition (ODIR) dataset, comprising 7000 samples of various eye conditions.	• Transfer learning techniques were employed to enhance model performance with limited data. • The best results were achieved using MobileNet with the Adam optimiser, yielding 89.64% accuracy.	• The MobileNet model with the Adam optimiser achieved a testing accuracy of 89.64%.
[5]	• The study utilized the GoDARTS cohort, which includes 10,149 individuals with type 2 diabetes and 8,157 without diabetes at recruitment. • A total of 6,127 individuals with type 2 diabetes had available retinal photographs, forming the primary dataset for analysis.	• A deep-learning artificial intelligence model was developed to predict cardiovascular disease outcomes from diabetic retinal screening images. • The retinal images were analyzed using an EfficientNet-B2 network for predicting 10-year cardiovascular risk.	• The retinal risk score performed similarly to the PCE (AUC 0.697). • Combining the AI-derived retinal risk with the PCE improved prediction (AUC 0.728).
[6]	• The primary dataset used is the KAGGLE dataset, containing 35,126 retinal fundus images. • The KAGGLE dataset includes five classes: one healthy and four diabetic retinopathy stages. • An external validation was performed using the same KAGGLE dataset, selecting 100 images from each class.	• The methodology involves three stages: image acquisition, model development, and model evaluation. • Fundus images are retrieved from reliable sources for classification. • Stacked auto-encoders are utilized for data compression and reconstruction. • Data augmentation techniques are employed to address class imbalance.	• The model achieved an overall accuracy of 79.5% on the external dataset, predicting 443 out of 500 test images correctly. • Precision across all classes was 88.6%, indicating reliable predictions with minimal false positives. • The highest training accuracy reached 93%, while testing accuracy was 88% with a 75:25 split.
[7]	• The study utilizes the Diabetic Retinopathy 224x224 Gaussian Filtered dataset from Kaggle, containing pre-processed retina images for diagnosis and grading. • Images in the dataset are categorized into five classes: Mild NPDR, Moderate NPDR, Severe NPDR, PDR, and No_DR.	• The methodology includes creating a web-based form for user registration, login, and image upload. • A Convolutional Neural Network (CNN) algorithm is employed to classify retinal images into five diabetic retinopathy stages. • The system integrates predictive models into the web application for user health management.	• The research developed a robust and efficient system for image classification using Convolutional Neural Networks (CNN). • CNN demonstrated superior accuracy and efficiency compared to other algorithms. • The system effectively implemented functionalities like login, registration, and reliable file uploads.
[8]	• The study utilized data from 181 patients, combining both tabular and Optical Coherence Tomography (OCT) image data. The dataset was split into training and test sets, with 126 patients in the training set and 55 in the test set.	• The model integrates Optical Coherence Tomography (OCT) images and clinical data from 181 patients. • It combines convolutional neural networks (CNNs) for image data with multi-layer perceptron (MLP) for tabular clinical data.	• The hybrid deep learning model achieved an accuracy of 85% and an AUC-ROC score of 0.89, indicating strong predictive power.

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III. DEEP LEARNING TECHNIQUES

Deep learning has become a powerful tool for the prediction of diabetic retinopathy (DR), leveraging advanced neural network architectures to analyze retinal images and estimate disease severity [9]. Convolutional Neural Networks (CNNs) are supreme among commonly used methods, given their ability to learn automatically from retinal fundus images [10]. CNN-based models such as VGG16, ResNet, Inception, and EfficientNet have been shown to demonstrate higher accuracy in diabetic retinopathy classification through the detection of intricate patterns in retinal abnormalities.

Recurrent Neural Networks (RNNs) and more advanced variants, e.g., Long Short-Term Memory (LSTM) networks, have been explored for sequential data processing, particularly in the assimilation of temporal data from repeated eye scan at different times [11]. Hybrid models that combine CNNs with RNNs or LSTMs enhance prediction capabilities by assimilating both spatial and sequential data.

Transfer Learning is a common method where pre-trained models based on large picture datasets, including ImageNet, are adapted to diabetic retinopathy classification, thus significantly reducing the need for large amounts of labelled data [12].

Attention mechanisms and transformer models, including Vision Transformers (ViTs), have become popular due to their ability to focus on key regions in retinal images, improving interpretability and classification accuracy.

To overcome data scarcity, Generative Adversarial Networks (GANs) are employed for data enhancement, generating simulated retinal images for enhancing generalization of the model. Additionally, autoencoders and unsupervised learning techniques enable anomaly detection by identifying abnormalities from normal retinal morphology.

These deep learning approaches have significantly improved diabetic retinopathy prediction, offering computerized, accurate, and cost-effective diagnostic choices. However, challenges such as model interpretability, consistency of datasets, and real-world implementation require further advancement to allow widespread clinical usage.

IV. CHALLENGES AND FUTURE WORKS

The diabetic retinopathy (DR) prediction via deep learning faces many challenges in its widespread use in the clinic. An important one of these is that it requires massive, high-quality labelled datasets because deep learning networks require large volumes of training data to achieve high accuracy. However, carefully labelling medical images is time-consuming and requires involvement from experienced ophthalmologists and thus creates variability in labelling. In addition, deep learning models often face class imbalance issues, as mild diabetic retinopathy instances are underrepresented compared to severe cases, which affects model generalization. Another issue regards the interpretability of deep learning models; most models are black boxes, making it difficult for medical professionals to understand the logic behind their predictions. This lack of openness reduces trust and limits therapeutic deployment. In addition, variations in picture acquisition environments, such as various camera types, illumination levels, and patient position, create uncertainty that deep learning models need to handle skilfully. Achieving robustness across heterogeneous data sets is a challenge, particularly when deploying models in different healthcare institutions with varying imaging modalities.

Computational complexity is a significant hindrance, since advanced deep learning models require enormous processing power, thereby limiting their deployment in low-resource environments, e.g., rural clinics. Further, overfitting is a common issue where models show exceptional performance on training data but are unable to generalize to new cases, thereby lowering their practical usefulness. Fixing this requires extensive regularization strategies and data augmentation methods. In addition, ethical and regulatory concerns pose adoption challenges. Protecting patient privacy and data security is important when handling sensitive medical images, and compliance with regulations like HIPAA and GDPR makes model adoption cumbersome. Bias in AI models is also a major concern, as models optimized on specific demographic data might demonstrate uneven performance across different groups, leading to potential healthcare disparities. Future work will need to focus on a number of key areas in order to increase the effectiveness and reliability of diabetic retinopathy prediction through deep learning.

One promising area is the development of self-supervised and semi-supervised learning techniques, which can reduce dependence on large labelled datasets by making better use of unlabelled data. Transfer learning and domain adaptation can strengthen models' generalization across different imaging conditions. In addition, integration of explainable AI (XAI) techniques is critical for enhancing model interpretability so that physicians can understand and trust AI-based predictions.

Techniques such as attention mechanisms, saliency maps, and gradient-based visualization can help clarify the models' decision-making processes. A key area of focus for future activity is model robustness through the generation of diverse and standardized datasets that realistically represent global populations. Federated learning, which supports model training on different institutions without sharing patient data, promotes generalization while maintaining privacy.

Additionally, enhancing deep learning models for deployment in resource-limited environments is essential. This involves developing light models that require less processing resources without sacrificing high accuracy. Techniques like model quantization and trimming can support the achievement of this goal. In addition, multimodal learning techniques that combine retinal images with ancillary clinical information such as patient history, blood glucose values, and genetic factors can enhance predictive performance. Incorporating deep learning models into telemedicine platforms increases accessibility, making early detection of diabetic retinopathy possible in rural areas. In addition, continuous surveillance and model updates are necessary to adapt to new data and evolving disease patterns.

Future initiatives should focus on ethical AI development through ensuring fairness, reducing biases, and following healthcare norms. Collaboration between AI researchers, ophthalmologists, and regulatory bodies is essential to improve deep learning-based diabetic retinopathy prediction models for real-world clinical use. While deep learning has been highly promising in the automation of diabetic retinopathy detection, overcoming these challenges and advancing future research directions will be essential for achieving reliable, interpretable, and accessible AI-based healthcare solutions.

V. CONCLUSION

Diabetic retinopathy (DR) is a leading cause of vision loss worldwide, which needs to be detected and diagnosed with urgency as well as accuracy for best management. The review has highlighted the advancement of deep learning algorithms for predicting diabetic retinopathy, emphasizing their ability to improve diagnostic accuracy, reduce reliance on human screening, and enhance health care accessibility. Future work should focus on improving model robustness through federated learning, semi-supervised learning, and domain adaption techniques. Furthermore, improving model interpretability through explainable AI techniques will enhance trust among healthcare professionals. Using multimodal data sources such as clinical information and patient history could improve accuracy in prediction. Coordination between medical doctors, artificial intelligence researchers, and regulatory officials is important in order to optimize deep learning-diabetic retinopathy prediction algorithms and ensure they are used safely and effectively within clinical settings. Despite challenges faced today, deep learning continually revolutionizes the detection of diabetic retinopathy and offers an encouraging pathway towards early diagnosis, timely intervention, and improved patient outcomes.

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Impact Factor 8.102 ⧖ Peer-reviewed & Refereed journal ⧖ Vol. 14, Issue 3, March 2025

DOI: 10.17148/IJARCCE.2025.14342

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