International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 • Website: www.ijfmr.com • Email: editor@ijfmr.com

Early Diabetic Retinopathy Detection Using Deep CNNs on Fundus Images

Yash Chiragkumar Shah[1], Krushang Tanti[2], Yogesh Kumar[3]

[1,2]Student, Department of CSE, School of Technology, Pandit Deendayal Energy University, Gandhinagar, India
[3]Assistant Professor, Department of CSE, School of Technology, Pandit Deendayal Energy University, Gandhinagar, India

Abstract
Diabetic Retinopathy (DR) is a retinal disease caused by diabetes that, if not diagnosed early, can cause blindness. In this study, we present a novel deep learning technique to detect and classify diabetic retinopathy through retinal fundus images. In order to divide diabetic retinopathy into five categories: No_DR, Mild, Moderate, Severe and Proliferative_DR, six architectures CNN1D, CNN2D, VGG16, MobileNetV2, ResNet and DenseNet were used. According to the results of the work, DenseNet performed best in training by acquiring 84.39% training accuracy with a loss of 0.4092. At the same time, MobileNetV2 performed best in validation by acquiring 78.85% validation accuracy with a loss of 0.5923. DenseNet attained the most remarkable performance in class No_DR and Mild with classification F1-scores of 0.95 and 0.65 respectively. According to this work, AI based models are accurate in detecting and classifying the diabetic retinopathy. Moreover, it showcases the capabilities of DenseNet for early detection and clinical screening to be the most reliable and generalizable model.

Keywords: Diabetic Retinopathy, Deep Learning, CNN, DenseNet, MobileNetV2, Fundus Images, Classification

1. Introduction

Diabetic Retinopathy (DR) is an eye disease related to diabetes which affects progressively the retina and it is one of the leading causes of preventable blindness in the whole world. It impairs an individual's sight and quality of life, leading to a disturbance in the daily activities. It develops over time because prolonged elevated blood sugar can damage the blood vessels in the retina, resulting in their leakage, swelling or formation of abnormal new vessels. Not only does this detriment vision but over the long-term becomes problematic if it goes undiagnosed or untreated [1]. DR can be classified into mild, moderate, severe non-proliferative DR (NPDR) and proliferative DR (PDR), with the latter two termed as advanced stages of PDR, in which PDR is considered as more serious than diabetic Macular Edema (DME) with a significant impact on vision loss [2]. Although all these stages are interconnected, their symptoms and progression vary, making it necessary to detect it at the correct time.

Patients with DR may not have any symptoms in the beginning, but as the disease progresses, they may develop blurry vision, floaters or may become completely blind if the condition is severe. What is particularly disturbing about DR is that it is asymptomatic and patients are often diagnosed at a late stage of the disease [3]. It was reported in world health's reports that about one-third of the diabetic population are affected by DR and among them a significant number have vision-threatening stages [4]. Therefore, early detection and grading of DR are crucial to prevent irreversible loss of vision and timely intervention.

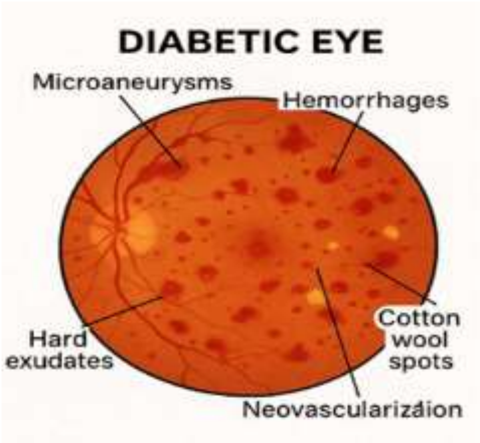

Figure 1: Features of a DR Eye

Traditional methods for diagnosing DR include taking pictures of the retina and having eye specialists grade them manually, using fluorescein dye to see blood vessels, and using optical coherence tomography to get detailed images. However, these methods have some problems. They often need experts to interpret the results, can be expensive, and are not easy to use for large screenings, especially in areas with limited resources [5]. To address these issues, AI and machine learning (ML) provide helpful options. With access to many retinal images, ML and deep learning models can automatically find signs of DR and classify its severity with high accuracy. This reduces needing manual review [6]. Convolutional Neural Networks (CNNs) and other advanced deep learning models can extract retinal features such as blood vessel abnormalities, microaneurysms, and exudates, enabling automated severity classification and risk prediction [7]. Such AI-driven frameworks not only improve diagnostic efficiency but also pave the way for scalable, cost-effective, and personalized screening approaches.
Therefore, in this paper, a deep learning-based model has been proposed for the detection and classification of diabetic retinopathy across its various stages, as well as distinguishing between normal and diseased retinal conditions.
The rest of the paper is organized as follows: Section 2 presents the Literature Review, Section 3 describes the proposed methodology, Section 4 discusses the performance of the applied classifiers, and Section 5 concludes and highlights future directions.

2. Literature Review

The retina in diabetic retinopathy (DR) is considered one of the most predicted areas to be analysed by artificial intelligence (AI) to answer the medical image analysis challenge, which is an important issue that requires early detection and the presence of retinal datasets as compared to other domains. Abdelneam [1] carried out an extensive systematic review and meta-synopsis of AI-based screening systems and the usual manual screening methods. The paper established that AI algorithms were as sensitive and specific as, and in most instances superior to, manual grading and would potentially help in decreasing diagnostic workload on ophthalmologists.
Based on this, Akhtar et al. [2] introduced a deep learning-based model, with the purpose of directly grading DR. They used convolutional neural networks (CNNs) which were trained on extensive annotated

data giving strong results in most levels of severity of DR. This paper had the effect of defining the viability of automated severity classification, which is especially applicable in contexts that are resource-constrained and where expert graders might be unavailable. Alqahtani et al. [3] also offered complementary evidence by conducting another systematic review and meta-analysis to assess the overall effectiveness of AI in screening of DR. Their results solidified the perception that AI systems are consistently high in accuracy and reliability in diverse populations and different imaging circumstances. Notably, they put significant importance on the scalability of AI-based screening that might allow large-scale population screening programs and an intervention at the early stages.

A meta-analysis of the effectiveness of AI-based systems in the screening of DR was conducted by Alqahtani et al. [4]. They emphasized that the diagnostic accuracy of the tools used was considerably high, especially in the metrics of sensitivity and specificity, and thus AI-related tools can be regarded as similar to ophthalmologists and can be applied to mass screening programs. This has solid clinical reasoning as to why AI systems should be used in real-life screening programs, particularly in those areas where specialists are scarce.

A review of deep learning applications in DR detection was provided by Alyoubi et al. [5]. In their research, they mentioned different CNN structures, preprocessing techniques and data augmentation techniques that can be used to enhance classification performance considerably. Notably, they observed that factors of inconsistency in image quality, imbalance in the dataset, and the necessity of generalizable representations of the models across different populations are acute concerns. Bhulakshmi and Rajput [6] conducted a systematic review on DR detection and classification on fundus images. The survey includes different types of deep learning models like CNNs, transfer learning models, and ensemble models. The authors stressed the fact that, although these techniques are highly accurate in laboratory conditions, application to a clinical population needs to be highly validated using multi-institutional data.

Recently Dejene et al. [7] conducted a general system review of DR screening based on machine learning techniques. In contrast to the deep learning-related polls, their article included classical machine learning techniques as well as contemporary neural ones. This holistic view demonstrated that despite dominant practices in the field, deep learning leads in computing, and besides critical designing of features, traditional approaches can also be adequate. Beyond systematic reviews, Duggal et al. [8] conducted a validation and implementation study of AI-based DR screening in the public health environment. Their results validated the clinical soundness of AI tools during screening of large populations, and also revealed obstacles like workflow integration, acceptance by healthcare employees and infrastructure preparedness. In terms of methodology, Khan et al. [9] investigated the importance of retinal blood vessel segmentation in improving deep learning in the diagnosis of DR. Their study underlined that preprocessing using proper segmentation of vasculature structures facilitates networks to record disease-specific biomarkers more effectively. To cover the need for resource-saving solutions, Kim et al. [10] offered a lightweight multi-deep learning model that could detect DR as well as recognize levels of severity. In the article by Lam et al. [11], one of the earlier examples of deep learning applied to automated DR detection was revealed. Muhammed and Rashid [12] used Bayesian deep learning to detect diabetic retinopathy along with uncertainty evaluation, such that the model not only assesses the severity of the disease but also provides an estimation of its detectability. Shekar et al. [13] offered a review of deep learning methods of DR detection and grading, discussing different CNN-based architectures and transfer learning techniques. Finally, Thanikachalam et al. [14] developed a framework of deep CNN to detect and classify DR and diabetic macular edema (DME) jointly, demonstrating better sensitivity and specificity on various benchmark datasets than typical CNN architectures.

3. Methodology

3.1 Data Collection and Preprocessing

For classification of diabetic retinopathy fundus image dataset from no diabetic retinopathy to proliferative diabetic retinopathy, data in the form of coloured fundus images with high resolution was utilized. Publicly available images that are clinically validated were used to enhance reliability and diversity. As the retinal image size, illumination and contrast can vary naturally, a complete preprocessing pipeline was created to assist the model in performing and generalizing better.

At first, all images were resized to 224 x 224 pixels to allow consistency between the models like VGG16, MobileNetV2, and DenseNet which have fixed input dimensions. Then, normalization was used on the pixels to speed up the training process and stop gradients from exploding by making them between 0 and 1. Augmentations were applied to the data so that overfitting would be avoided. Some of the augmentations that were employed included horizontal and vertical flips, random rotations, zooming, brightness and contrast adjustment as well as minor translations. Through these changes, the models acquire generalized properties of the retina that are not sensitive to the specifics of the picture acquisition conditions.

To estimate objectively the model performance, the dataset was separated into training, validation and testing sets. Each of them was trained with 20 epochs through early stopping when the loss on the validation set is low, to achieve good convergence. A number of architectures used batch normalization and dropout regularization to stabilize the learning process and reduce variance. In all, the preprocessing stage was vital in improving the quality and diversity of input data, which could help the deep learning models to extract discriminatory retinal features important to correctly identify and classify diabetic retinopathy.

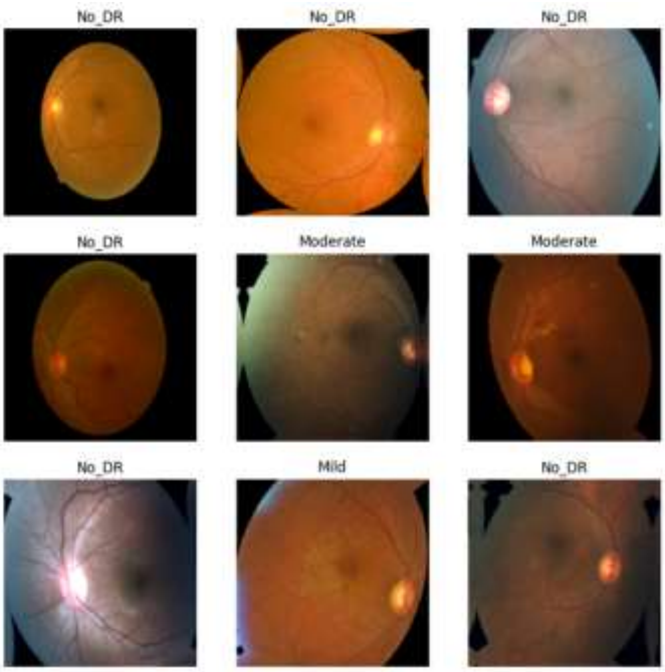

Figure 2: Sample Images after Augmentation and Normalization

3.2 Segmentation Techniques for Image Data

The purpose of image segmentation of diabetic retinopathy is to detect and isolate certain fundal image features such as blood vessels, exudates, haemorrhages, or microaneurysms. This is where automated diagnosis and the severity of the disease is monitored. K-means, Canny Edge, Adaptive Mean Threshold, Adaptive Gaussian Threshold, Otsu, GrabCut, Watershed and U-net are popular segmentation models that can be used in this task.

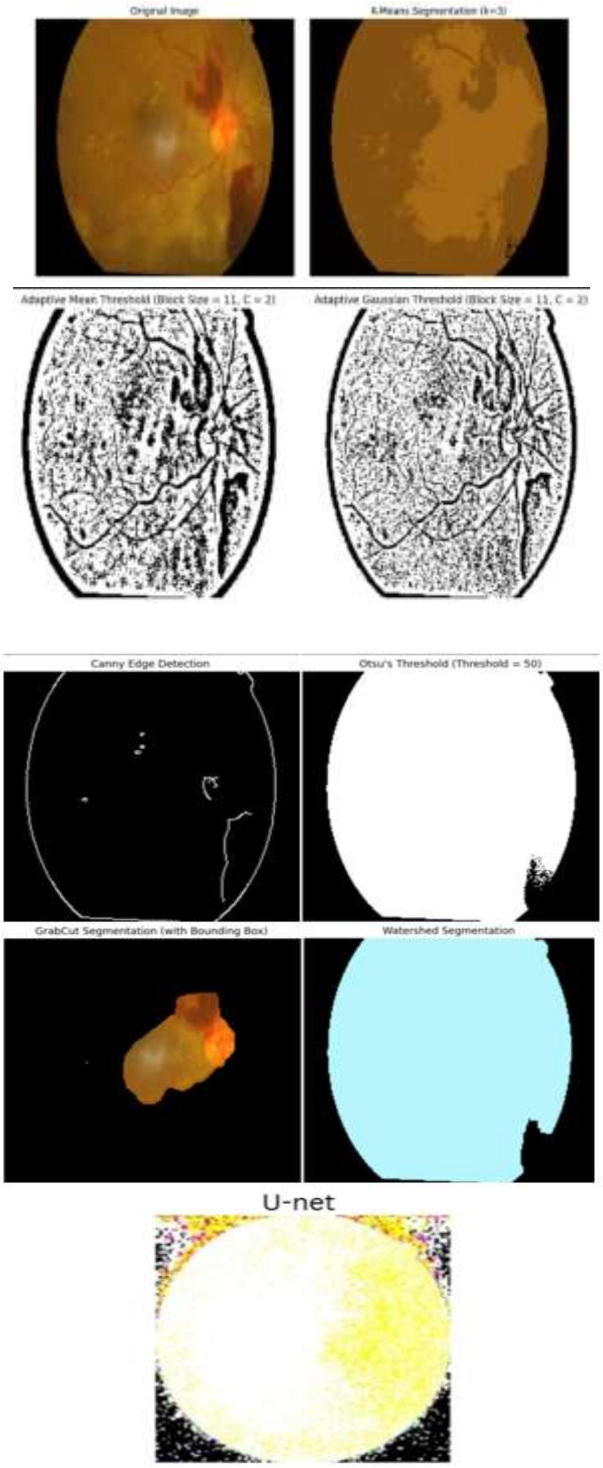

Figure 3: Segmentation Output Samples

3.3 Applied Models for Detection of DR

In order to obtain full and reliable extraction of features in retinal images, six deep learning architectures - CNN1D, CNN2D, VGG16, MobileNetV2, ResNet, and DenseNet - were applied and systematically tested for the classification of the levels of diabetic retinopathy. The goal of using multiple architectures was to assess the capacity of architectures to both capture the fine-grained characteristics of lesions and also general structural abnormalities that are present in the pre-processed images from the fundus. Each model is trained and tuned under consistent experiment conditions in order to ensure the models are fairly compared.

CNN1D was used to look for sequential intensity changes amongst the pixel distributions that could be used to detect subtle changes in the texture and illumination patterns within the retina which may indicate abnormalities in the early stages. CNN2D introduced this analysis into the spatial domain, by learning localized two-dimensional patterns directly from the matrix of the image. Through convolutional operations it was able to capture clinically important features such as microaneurysms, haemorrhages and hard exudates that are important signs of the progression of disease.

The VGG16 architecture uses a deep stacked 3X3 convolutional layers to create hierarchical representations of features. This design meant that the network could gradually learn from low level visual features like edges and gradients up to more complex formations of retinal structure and pathological formations. MobileNetV2 presented an efficient architecture which was based on depth wise separable convolution architecture and inverted residual connection, which could greatly reduce computation cost while keeping good classification performance. This lightweight nature makes it especially well-suited for use in real-time screening systems, and for deployment in resource-constrained clinical environments.

ResNet introduced residual learning, the use of skip connections, to make it easier for the network to train with greater depth as it allows it to propagate gradients easily and to reduce vanishing gradient problems. This enabled the model to acquire complex representations of retinal content without performance degradation. DenseNet even improved the propagation of features by creating direct connections between all previous layers promoting the re-use of features and increasing the gradient flow through the network. Such dense connectivity proved to be useful in stabilising the training and enhancing generalization, in particular when dealing with small amounts of retinal images.

Collectively, the combination of these architectures and their integration and evaluation allowed both localized details about the lesions and global patterns of structure in the retina to be extracted. This comprehensive feature learning approach played a major role in the correct and reliable classification of diabetic retinopathy in multiple stages of severity.

4. Results

The findings of the study are reported in this section of various deep learning models that were used on classification of diabetic retinopathy. Similar models were evaluated according to performance in the validation datasets and training datasets. To see how well the models performed and how they generalized, class level F1 scores were used as the main criteria for evaluation. Different architectures ranging from simple CNNs to the more complex DenseNet and MobileNet were observed, and it was noted that model depth which in turn affects feature extraction had great impact on prediction accuracy.

Table 1: Model Performance Prediction for Diabetic Retinopathy Classification

Models	Training Accuracy	Training Loss	Validation Accuracy	Val. Loss
CNN1D	0.6992	0.8151	0.7008	0.8375
CNN2D	0.7151	0.7686	0.7363	0.7539
VGG16	0.8094	0.4955	0.7254	0.7267
MobileNetV2	0.7954	0.5583	0.7885	0.5923
ResNet	0.7973	0.5194	0.7387	0.8287
DenseNet	0.8439	0.4092	0.8263	0.5262

The table compares performance of six deep learning models: CNN1D, CNN2D, VGG16, MobileNetV2, ResNet, and DenseNet based on their training and validation accuracies and losses. DenseNet has the best learning performance among all other models with highest training accuracy of 0.8439 and lowest training loss of 0.4092. The best generalization is achieved with MobileNetV2 which has the best trade-off between a validation accuracy of 0.7885 and a validation loss of 0.5923. VGG16 trained well but overfit slightly with a noticeable decrease in validation accuracy. The shallow structures of the simpler models CNN1D and CNN2D resulted in fair results because these architectures are inefficient at extracting high-level features. In general terms, the most advanced models like DenseNet and MobileNetV2 yielded better results in performance and generalization.

Table 2: F1 Scores of All Models per Class

Models	NO_DR	Mild	Moderate	Proliferate_DR	Severe
CNN1D	0.51	0.05	0.37	0.00	0.00
CNN2D	0.51	0.09	0.29	0.23	0.00
VGG16	0.95	0.52	0.64	0.35	0.34
MobileNetV2	0.75	0.41	0.72	0.21	0.36
ResNet	0.50	0.31	0.33	0.29	0.28
DenseNet	0.95	0.65	0.74	0.49	0.51

The table shows F1-scores of different models across five diabetic retinopathy (DR) severity classes. DenseNet was found to be the most balanced and fairly accurate across all of the classes, standing out in performance specifically on No_DR (0.95) and Mild (0.65). VGG16 achieved also strong scores, especially in No_DR and Moderate cases, with a decrease in results for the more severe stages. MobileNetV2 also achieved competitive results with good generalization in the Moderate class. On the other hand, CNN1D, CNN2D and ResNet performed poorly in the highly severe grades of DR, showing almost zero score for Proliferate_DR and Severe. In general, DenseNet and VGG16 achieved better performance than other models.

4.1 Best Learning Curves

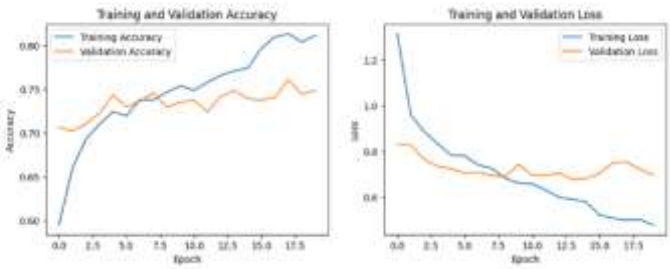

Figure 4: VGG16 Learning Curve

Both the training and validation accuracy show a steady upward trend, while the losses decrease consistently, indicating that the model learns effectively without major overfitting. The validation curve remains close to the training curve, suggesting good generalization to unseen data.

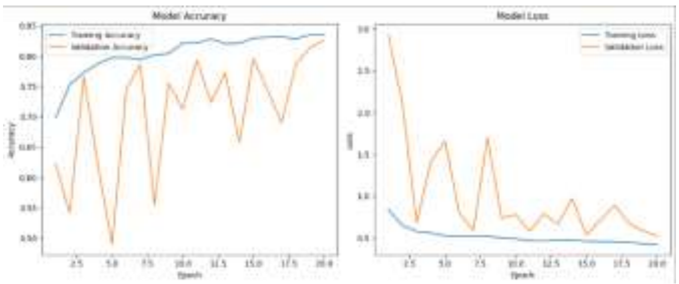

Figure 5: DenseNet Learning Curve

The training accuracy does not drop. Validation accuracy is also not too far away despite the slight fluctuation. The training loss is declining smoothly however the validation loss is a bit variable. This may be due to lack of data or class imbalance. In general, both networks have a powerful learning performance. In comparison, DenseNet has better stability while VGG16 has a more consistent convergence.

5. Conclusion

Using machine learning classifiers to detect and classify diabetic retinopathy has great potential for making efficient and accurate diagnostic systems. When retinal image datasets are utilized by these models, they can identify different stages of diabetic retinopathy and hence aid in diagnosis, early intervention and treatment. Despite having a strong performance, there are some limitations in performance such as variations in image quality, imbalance in dataset, limitation in generalizability on a diverse population, and reduced accuracy of some classifiers on complex cases. Future research needs to include large-scale, multi-institutional datasets and robust machine learning algorithms that are interpretable for clinical use to tackle these issues. In addition, screening for diabetic retinopathy can be made more accessible and accurate across the world by integrating optimization techniques and lightweight architecture for enhanced efficiency and scalability.

References

1. A.I. Abdelneam, "Artificial intelligence versus manual screening for the detection of diabetic retinopathy: a comparative systematic review and meta-analysis," no. May, pp. 1-14, 2025, doi: 10.3389/fmed.2025.1519768.
2. S. Akhtar et al., "A deep learning based model for diabetic retinopathy grading," pp. 1-20, 2025.
3. A.S. Alqahtani, W.M. Alshareef, H.T. Aljadani, W.O. Hawsawi, M.H. Shaheen, "The efficacy of artificial intelligence in diabetic retinopathy screening: a systematic review and meta-analysis," vol. 9, pp. 1-12, 2025.
4. A.S. Alqahtani, W.M. Alshareef, H.T. Aljadani, W.O. Hawsawi, M.H. Shaheen, "The efficacy of artificial intelligence in diabetic retinopathy screening: a systematic review and meta-analysis," vol. 9, pp. 1-12, 2025.
5. W.L. Alyoubi, W.M. Shalash, M.F. Abulkhair, "Diabetic retinopathy detection through deep learning techniques: A review," Informatics in Medicine Unlocked, vol. 20, 2020.
6. D. Bhulakshmi, D.S. Rajput, "A systematic review on diabetic retinopathy detection and classification based on deep learning techniques using fundus images," pp. 1-21, 2024, doi: 10.7717/peerj-cs.1947.
7. F.M. Dejene, T.G. Debelee, F. Schwenker, Y.M. Ayano, Diabetic retinopathy screening using machine learning: a systematic review. 2025.
8. M. Duggal, A. Chauhan, V. Gupta, A. Kankaria, D. Budhija, "Real-World Evaluation of AI-Driven Diabetic Retinopathy Screening in Public Health Settings: Validation and Implementation Study," vol. 13, 2025, doi: 10.2196/67529.
9. M.B. Khan, M. Ahmad, S.B. Yaakob, R. Shahrior, M.A. Rashid, H. Higa, "Automated Diagnosis of Diabetic Retinopathy Using Deep Learning: On the Search of Segmented Retinal Blood Vessel Images for Better Performance," 2023.
10. K.S. Kim, M.U. Ali, J.H. Byun, S. Kim, S. Kim, "A lightweight multi-deep learning framework for accurate diabetic retinopathy detection and multi-level severity identification," no. April, pp. 1-11, 2025, doi: 10.3389/fmed.2025.1551315.
11. C. Lam, D. Yi, M. Guo, T. Lindsey, "Automated Detection of Diabetic Retinopathy using Deep Learning," pp. 147-155.
12. M. Muhammed, H. Rashid, "Bayesian deep learning applied to diabetic retinopathy with uncertainty quantification," Heliyon, vol. 11, no. December 2024, 2025.
13. S. Shekar, N. Satpute, A. Gupta, "Review on diabetic retinopathy with deep learning methods," vol. 8, no. 6, 2021, doi: 10.1117/1.JMI.8.6.060901.
14. V. Thanikachalam, K. Kabilan, S.K. Erramchetty, "Optimized deep CNN for detection and classification of diabetic retinopathy and diabetic macular edema," BMC Medical Imaging, pp. 1-17, 2024, doi: 10.1186/s12880-024-01406-1.