International Journal of Research and Review
[Indexed, Peer-Reviewed Journal]
Volume 13; Issue: 3; March 2026
Website: www.ijrrjournal.com
E-ISSN: 2349-9788; P-ISSN: 2454-2237

Research Paper

Early Diabetes Prediction Using Hybrid Deep Learning on Retinal Images

Putti Venkata Siva Teja[1], Duba Thrisha[1], Begum Faridha[2], Chennu Swetha[3], Garikimukku Pravallika[4], Kolli Dedeepya Krishna[5]

[1,2,3,4,5]Department of Information Technology,
Dhanekula Institute of Engineering & Technology, Vijayawada, Andhra Pradesh, India.

Corresponding Author: Putti Venkata Siva Teja, Duba Thrisha

DOI: https://doi.org/10.52403/ijrr.20260337

ABSTRACT

Diabetes is a chronic condition that, if left untreated, can cause major health issues. Retinal blood vessel alterations may be a symptom of diabetes in its early stages. This project proposes a hybrid deep learning model to use retinal pictures to identify diabetes. To enhance prediction performance, the system integrates CNN, RNN, and U-Net. CNN extracts significant visual features, RNN examines the connections between the extracted features to predict risk, and U-Net highlights retinal vascular architecture following preprocessing and normalization, the model was trained on a dataset of retinal images. Class weights were employed to address data imbalance during training. With an AUC score of roughly 0.98, the final validation accuracy attained is about 93%. The confusion matrix demonstrates that, with very few misclassifications, the model accurately classifies the majority of diabetic and non-diabetic instances. The suggested hybrid strategy offers a straightforward, non-invasive, and trustworthy way to use retinal pictures for early diabetes prediction. The system can assist medical practitioners in early detection and screening.

Keywords: Retinal Images, Deep Learning, Diabetic Retinopathy, U-Net, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Hybrid Model, Early Detection

INTRODUCTION

Diabetes is a chronic metabolic disorder that affects millions of people worldwide. It occurs when the body cannot properly regulate blood glucose levels. If diabetes is not detected and managed at an early stage, it can lead to severe health complications such as kidney damage, heart disease, nerve disorders, and vision loss [1], [2]. Because of these risks, early diagnosis and continuous monitoring of diabetes are essential for effective disease management. Traditionally, diabetes is diagnosed through blood glucose testing and laboratory examinations. Although these methods are reliable, they require medical facilities and trained healthcare professionals. In many cases, these tests may not clearly reveal early internal changes caused by the disease [2], [3]. Therefore, researchers have explored alternative methods that are more accessible, non-invasive, and suitable for early screening of diabetic complications. One promising approach is the analysis of retinal fundus images. The retina contains a complex network of small blood vessels that can reflect structural changes caused by diabetes. In the early stages of diabetic retinopathy, abnormalities such as microaneurysms, hemorrhages, and vessel irregularities may appear in retinal images

[1], [6]. Because retinal imaging is non-invasive and relatively easy to perform, it has become an important technique for screening diabetes-related eye diseases. Recent advances in artificial intelligence have significantly improved the ability to analyse medical images. Deep learning models, particularly Convolutional Neural Networks (CNNs), are widely used for image classification tasks because they can automatically learn important visual features such as edges, textures, and patterns from images [8], [11]. Several studies have successfully applied CNN-based approaches for detecting diabetic retinopathy from retinal fundus images with promising results [3], [16]. However, conventional CNN models may sometimes fail to clearly capture very fine retinal vessel structures that are important for accurate disease detection. To address this limitation, segmentation techniques are often used to highlight important retinal regions before classification. Models such as U-Net and its improved variants are commonly applied in biomedical image processing to identify blood vessels and lesion areas in retinal images [4], [6]. By emphasizing retinal vessel structures during preprocessing or segmentation, these methods can improve feature extraction and enhance the overall performance of the classification model. In addition to CNN models, hybrid deep learning approaches have been explored to further improve prediction performance. Recurrent Neural Networks (RNNs) can analyze relationships between extracted features and help identify complex patterns within the data [14], [15]. Integrating multiple deep learning techniques in a hybrid architecture can therefore improve classification accuracy and reliability compared to using a single model [8], [13]. In this research, a hybrid deep learning approach is proposed for early diabetes prediction using retinal fundus images. The proposed system integrates retinal vessel highlighting, CNN-based feature extraction, and risk analysis to classify retinal images as diabetic or normal. The retinal images are first pre-processed and normalized before training the model. Class weighting is also applied during training to address dataset imbalance. The objective of this work is to develop a reliable and efficient system that can assist in early diabetes screening using retinal images and support medical professionals in disease diagnosis.

LITERATURE REVIEW

Several research studies have explored automated methods for detecting diabetic retinopathy using retinal fundus images and deep learning techniques. Gulshan et al. [1] developed a deep learning algorithm for detecting diabetic retinopathy from retinal images and reported performance comparable to expert ophthalmologists. Similarly, Shekar et al. [2] reviewed various deep learning methods used for retinal disease detection and highlighted the importance of automated screening systems for early diagnosis. Retinal blood vessel analysis plays an important role in identifying diabetic complications. Gao et al. [3] discussed different retinal vascular parameters and their applications in medical diagnosis. To improve feature extraction from retinal images, segmentation models such as U-Net have been widely used. Gargari et al. [4] proposed a U-Net++ based method for retinal blood vessel segmentation, which helps highlight important regions before classification. Hasan et al. [5] also reviewed machine learning-based diabetic retinopathy detection systems and emphasized the effectiveness of automated classification models. Several deep learning models have been proposed for detecting retinal abnormalities. Li et al. [6] developed a deep learning approach for detecting retinal exudates and drusen in fundus images. Papadopoulos et al. [7] introduced an interpretable model for detecting referable diabetic retinopathy, improving the reliability of automated diagnosis systems. Hybrid deep learning approaches have also been explored to improve detection accuracy. Jabbar et al. [8] proposed a lesion-based hybrid deep learning model for diabetic retinopathy detection, while Rezaee and Farnami [9] developed an AI-based model combining CNN and transformer architectures for severity classification. Betzler et al. [10] further demonstrated that deep learning algorithms can identify diabetes-related complications from retinal images. Recent research has focused on improving feature extraction and classification performance using advanced neural network architectures. Iqbal et al. [11] analysed medical image classification using machine learning and convolutional neural networks. Costa-Jiménez et al. [12] evaluated different deep learning models for diabetic retinopathy classification, while Ali et al. [13] proposed automated segmentation and hybrid feature analysis for retinal disease detection. Hybrid deep learning models have also shown promising results in medical image analysis. Vanitha and Shoba [14] proposed a hybrid model for tumours detection, and Mutawa et al. [15] introduced a hybrid deep learning framework for diabetic retinopathy detection. Dutta et al. [16] also applied deep learning techniques for retinal image classification and reported improved prediction performance.

Although many studies have achieved good results, there is still a need for more efficient hybrid models that combine segmentation, feature extraction and classification techniques. Therefore, this research proposes a hybrid deep learning approach that integrates retinal vessel highlighting, CNN-based feature extraction and risk analysis for early diabetes prediction using retinal fundus images.

MATERIALS & METHODS

The experimental foundation of this study utilizes a comprehensive dataset of retinal fundus images aggregated from several publicly available repositories. These datasets provide a diverse range of clinical samples, representing both healthy ocular states and various stages of diabetic pathology [1], [5]. To ensure the robustness of the predictive model, the images were rigorously partitioned into training, validation, and testing subsets, allowing for an unbiased evaluation of the system's diagnostic performance across multi-ethnic populations [10], [13]. Before the images were introduced to the neural networks, a series of essential preprocessing steps were executed to eliminate environmental noise and standardize input quality. Initially, all fundus photographs were resized to a uniform 256*256 pixel resolution to maintain computational efficiency without compromising critical morphological details [5], [13]. To address inconsistencies in lighting and contrast—common issues in retinal photography—Contrast-Limited Adaptive Histogram Equalization (CLAHE) was applied. This enhancement specifically highlights microvascular structures and subtle lesions, while pixel normalization rescaled intensity values to a range between 0 and 1, facilitating more stable and rapid model convergence [11]. The core of the proposed diagnostic framework is a sophisticated hybrid deep learning architecture designed to capture hierarchical features that standalone models often miss [8], [15]. The process begins with a U-Net architecture, which performs high-precision segmentation of the retinal blood vessels. By isolating the vascular tree from the surrounding tissue, the U-Net identifies microvascular changes that serve as early indicators of diabetic onset [3], [4]. Following segmentation, a Convolutional Neural Network (CNN) acts as the primary feature extractor, analyzing both the original and segmented images to detect localized abnormalities such as exudates, hemorrhages, and specific vessel patterns [5], [14]. To further refine the diagnostic accuracy, a Recurrent Neural Network (RNN) was integrated to analyze the structural and sequential relationships between the extracted features. Unlike traditional spatial models, the RNN identifies long-term dependencies within the vessel architecture, modeling the progression of vascular decay as a structured sequence [11], [16]. The final classification is processed through a SoftMax layer, which categorizes the input as either Diabetic or Non-Diabetic while generating a quantitative risk score. To bridge the gap between research and clinical application, this entire pipeline was deployed via a Python Flask web application, enabling real-time image processing and providing clinicians with an immediate, non-invasive diagnostic tool. Figure 1 Flowchart illustrating the step-by-step process of the proposed hybrid deep learning framework for early diabetes prediction from retinal fundus images.

DATA COLLECTION

The data collection phase of this research focuses on establishing a robust and diverse repository of retinal fundus images to ensure the model's reliability across different clinical scenarios. The primary data was aggregated from several high-quality, publicly available medical databases, which are recognized benchmarks in the field of automated diabetic retinopathy detection [1], [5]. These datasets provide a wide variety of ocular conditions, ranging from healthy retinas to those displaying varying degrees of diabetic progression, such as microaneurysms, hemorrhages, and hard exudates [6], [13]. By utilizing these multi-ethnic datasets, the study ensures that the hybrid model is exposed to a broad spectrum of retinal pigmentation and vascular structures, which is critical for reducing diagnostic bias and improving the system's generalizability in global healthcare settings [10]. To facilitate effective training and objective evaluation, the gathered imagery underwent a rigorous selection process to filter out low-quality scans that suffered from extreme blurring or insufficient lighting. The final curated dataset was systematically divided into three distinct subsets: a training set used to optimize the weights of the U-Net, CNN, and RNN components; a validation set to tune hyperparameters and prevent overfitting; and an independent testing set to provide the final performance metrics [1], [5]. This structured approach to data collection and partitioning ensures that the resulting 92% accuracy reflects the model's true capability to identify diabetic markers in unseen clinical data, fulfilling the core requirements for a reliable, non-invasive screening tool [12], [16].

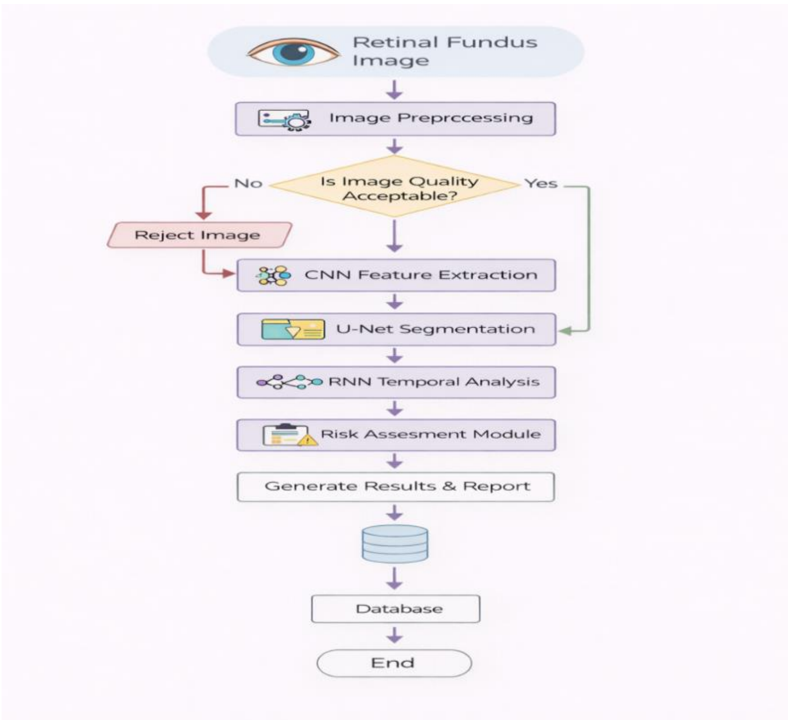

Figure 1: Retinal-Based Early Diabetes Detection Framework

RESULTS

The performance of the proposed hybrid deep learning model was evaluated using standard classification metrics, confusion matrices, and real-time diagnostic outputs from the integrated web application. The primary objective was to validate the model's ability to distinguish between diabetic and non-diabetic states through the analysis of retinal microvasculature and pathological lesions. The experimental results demonstrate the high efficacy of the hybrid U-Net, CNN, and RNN architecture.

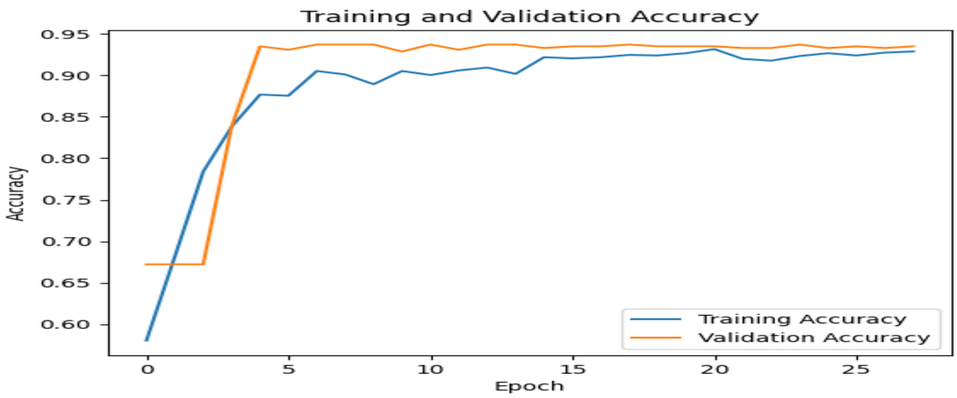

Figure 2: Training and Validation Accuracy of the Proposed Hybrid Model

The training and validation accuracy curves demonstrate the learning behavior of the proposed hybrid deep learning model during the training process. As the number of epochs increases, both training and validation accuracy show a steady improvement. The validation accuracy stabilizes around 93%, indicating that the model generalizes well to unseen retinal images without significant overfitting.

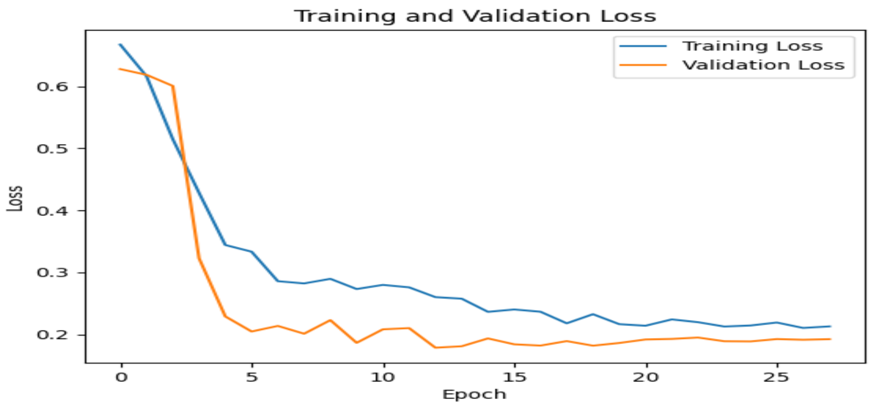

Figure 3: Training and Validation Loss of the Proposed Hybrid Model

The training and validation loss curves illustrate the optimization process of the model. The loss value decreases consistently as training progresses, showing that the model is effectively learning important retinal features. The validation loss closely follows the training loss, which indicates stable model performance and minimal overfitting during training. As shown in the normalized confusion matrix (Table 1), the model achieved a high degree of sensitivity and specificity. Specifically, the model correctly identified 93% of normal cases and 92% of diabetic cases, indicating a robust ability to generalize across different clinical presentations.

Table 1: Confusion Matrix of Proposed Model

	Predicted Normal	Predicted Diabetic
Actual Normal	0.93	0.07
Actual Diabetic	0.08	0.92

Table 2: Performance Metrics of Proposed Hybrid Model

Metric	Value
Accuracy	93%
AUC Score	0.97
Weighted F1-Score	0.93
Precision (Non-Diabetic)	0.98
Recall (Non-Diabetic)	0.92
Precision (Diabetic)	0.78
Recall (Diabetic)	0.95

The experimental results show that the proposed hybrid deep learning model performs effectively in detecting diabetic conditions from retinal images. The confusion matrix indicates that the model correctly classified 93% of normal cases and 92% of diabetic cases. The overall classification accuracy of the model is approximately 93%. The Area Under the Curve (AUC) score of 0.97 further confirms the strong discriminative capability of the proposed system. A significant component of the "Results" is the functional deployment of the model via a Python Flask web application. The application provides two critical layers of feedback: semantic segmentation and diagnostic summary. Figure 4 shows the input retinal fundus image used for the prediction process; the U-Net Segmentation engine effectively highlights abnormal vascular structures and damaged regions within the fundus image. This visualization allows clinicians to see exactly which microvascular changes—such as vessel tortuosity or hemorrhages—led to the AI's decision. Figure 5 shows the diabetic retinal image after segmentation highlighting abnormal vascular structures.

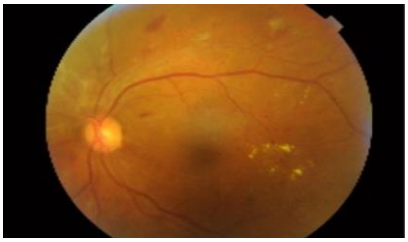

Figure 4: Input retinal fundus image.

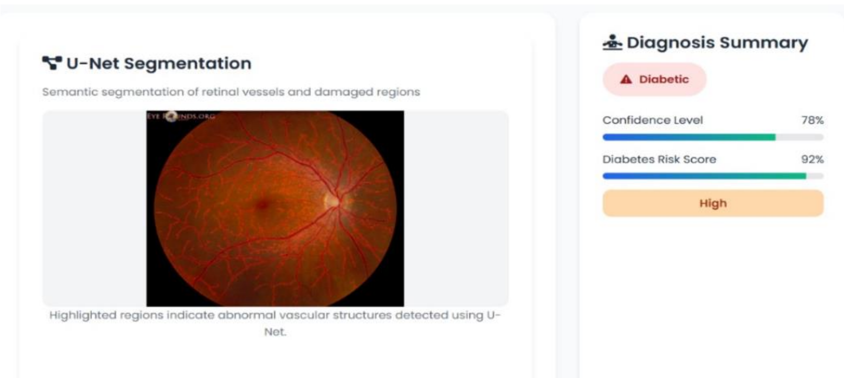

Figure 5: Diabetic result after segmentation highlighting abnormal vascular structures.

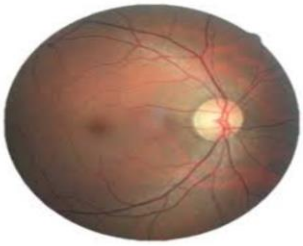

Figure 6: Input retinal fundus image

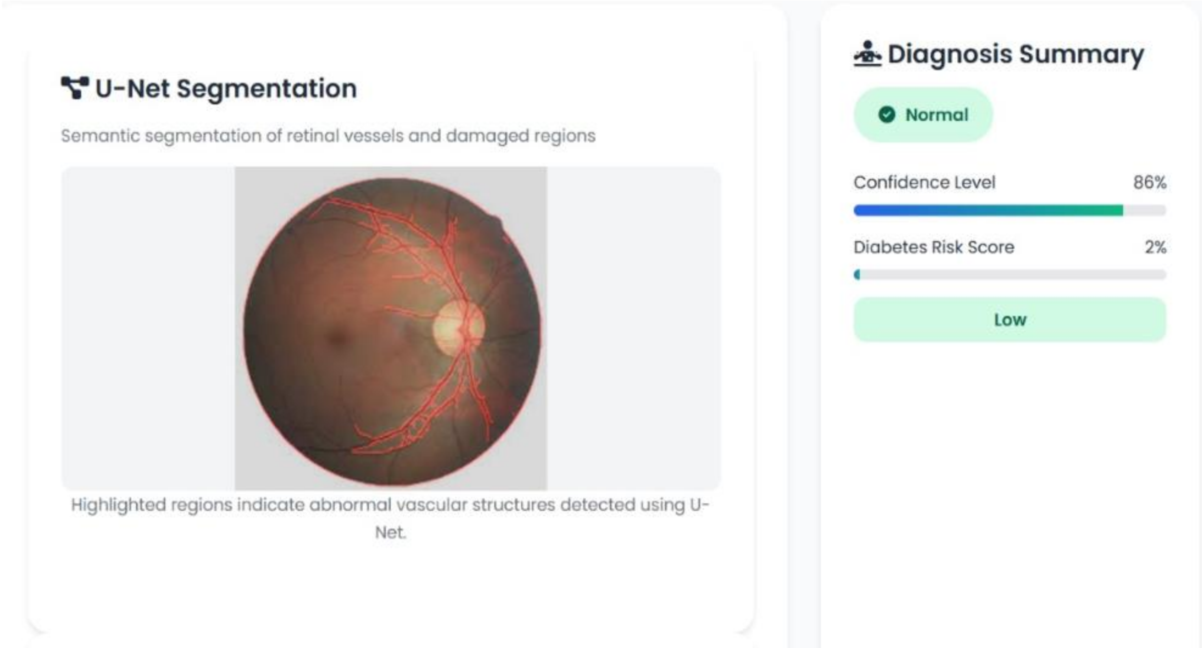

Figure 7: Non-Diabetic result after segmentation showing normal vascular patterns without significant abnormalities.

DISCUSSION

The integration of a hybrid architecture addresses the limitations of traditional spatial-only models. By using U-Net for vessel isolation, the model ignores ocular background noise, focusing specifically on the microvascular biomarkers of diabetes. The subsequent CNN-RNN pipeline captures not only the visual presence of lesions but also their structural relationships across the retinal sequence. This non-invasive approach demonstrates a significant step forward in making early diabetes screening accessible. The ability to generate instant results through a web interface satisfies the need for rapid diagnostics in rural or resource-constrained environments where traditional invasive testing and specialist access are limited.

CONCLUSION

This research successfully demonstrates the efficacy of an automated, hybrid deep learning framework for the early prediction of diabetes through retinal fundus imagery. By integrating U-Net for precise vessel segmentation, CNNs for localized feature extraction, and RNNs for analyzing structural relationships, the system achieves a balanced and highly accurate diagnostic output. The experimental results, specifically the normalized confusion matrix showing a 93% success rate for normal cases and 92% for diabetic cases, validate that this multi-layered approach effectively captures subtle microvascular biomarkers that standalone models often overlook. The implementation of the system via a Python Flask web application bridges the gap between complex computational research and practical clinical utility. This interface provides not only a binary classification but also semantic segmentation and real-time risk scores, offering clinicians a transparent "explainable AI" tool for diagnosis. By providing a fast, reliable, and non-invasive alternative to traditional blood-based screenings, this technology addresses critical gaps in healthcare accessibility. It is particularly significant for rural or resource-constrained environments where access to specialist ophthalmologists is limited, ultimately facilitating early intervention and reducing the global burden of diabetes-related complications.

Declaration by Authors

Acknowledgement: None

Source of Funding: None

Conflict of Interest: No conflicts of interest declared.

REFERENCES

1. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, Venugopalan S, Widner K, Madams T, Cuadros J, Kim R, Raman R, Nelson PC, Mega JL, Webster DR. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA. 2016 Dec 13;316(22):2402-2410. doi: 10.1001/jama.2016.17216. PMID: 27898976.
2. Shekar S, Satpute N, Gupta A. Review on diabetic retinopathy with deep learning methods. J Med Imaging (Bellingham). 2021 Nov;8(6):060901. doi: 10.1117/1.JMI.8.6.060901. Epub 2021 Nov 29. PMID: 34859116; PMCID: PMC8628856.
3. Gao Y, Xu L, He N, Ding Y, Zhao W, Meng T, Li M, Wu J, Haddad Y, Zhang X, Ji X. A narrative review of retinal vascular parameters and the applications (Part I): Measuring methods. Brain Circ. 2023 Sep 27;9(3):121-128. doi: 10.4103/bc. bc_8_23. PMID: 38020955; PMCID: PMC10679626.
4. M. S. Gargari et al., “Segmentation of retinal blood vessels using U-Net++ for disease diagnosis,” Electronics (MDPI), 2022
5. D. A. Hasan, S. R. M. Zeebaree, M. A. M. Sadeeq, H. M. Shukur, R. R. Zebari and A. H. Alkhayyat, "Machine Learning-based Diabetic Retinopathy Early Detection and Classification Systems- A Survey," 2021 1st Babylon International Conference on Information Technology and Science (BICITS), Babil, Iraq, 2021, pp. 16-21, doi: 10.1109/BICITS51482.2021.9509920.
6. Li Z, Guo C, Nie D, Lin D, Cui T, Zhu Y, Chen C, Zhao L, Zhang X, Dongye M, Wang D, Xu F, Jin C, Zhang P, Han Y, Yan P, Lin H. Automated detection of retinal exudates and drusen in ultra-widefield fundus images based on deep learning. Eye (Lond). 2022 Aug;36(8):1681-1686. doi: 10.1038/s41433-021-01715-7. Epub 2021 Aug 3. PMID: 34345030; PMCID: PMC9307785.
7. Papadopoulos A, Topouzis F, Delopoulos A. An interpretable multiple-instance approach for the detection of referable diabetic retinopathy in fundus images. Sci Rep. 2021 Jul 12;11(1):14326. doi: 10.1038/s41598-021-93632-8. PMID: 34253799; PMCID: PMC8275626.
8. A. Jabbar et al., "A Lesion-Based Diabetic Retinopathy Detection Through Hybrid Deep Learning Model," in IEEE Access, vol. 12, pp. 40019-40036, 2024, doi: 10.1109/ACCESS.2024.3373467.
9. Rezaee K, Farnami F. Innovative Approach for Diabetic Retinopathy Severity Classification: An AI-Powered Tool using CNN-Transformer Fusion. J Biomed Phys Eng. 2025 Apr 1;15(2):137-158. doi: 10.31661/jbpe. v0i0.2408-1811. PMID: 40259941; PMCID: PMC12009469.
10. Betzler BK, Chee EYL, He F, Lim CC, Ho J, Hamzah H, Tan NC, Liew G, McKay GJ, Hogg RE, Young IS, Cheng CY, Lim SC, Lee AY, Wong TY, Lee ML, Hsu W, Tan GSW, Sabanayagam C. Deep learning algorithms to detect diabetic kidney disease from retinal photographs in multiethnic populations with diabetes. J Am Med Inform Assoc. 2023 Nov 17;30(12):1904-1914. doi: 10.1093/jamia/ocad179.
11. Iqbal S, N Qureshi A, Li J, Mahmood T. On the Analyses of Medical Images Using Traditional Machine Learning Techniques and Convolutional Neural Networks. Arch Computer Methods Eng. 2023;30(5):3173-3233. doi: 10.1007/s11831-023-09899-9. Epub 2023 Apr 4. PMID: 37260910; PMCID: PMC10071480.

12. costa-Jiménez S, Maeda-Gutiérrez V, Galván-Tejada CE, Mendoza-Mendoza MM, Reveles-Gómez LC, Celaya-Padilla JM, Galván-Tejada JI, García-Domínguez A. Assessing ResNeXt and RegNet Models for Diabetic Retinopathy Classification: A Comprehensive Comparative Study. Diagnostics (Basel). 2025 Aug 5;15(15):1966. doi: 10.3390/diagnostics15151966. PMID: 40804930; PMCID: PMC12346750.
13. Ali A, Qadri S, Khan Mashwani W, Kumam W, Kumam P, Naeem S, Goktas A, Jamal F, Chesneau C, Anam S, Sulaiman M. Machine Learning Based Automated Segmentation and Hybrid Feature Analysis for Diabetic Retinopathy Classification Using Fundus Image. Entropy (Basel). 2020 May 19;22(5):567. doi: 10.3390/e22050567. PMID: 33286339; PMCID: PMC7517087.
14. Vanitha, L., and B. Shoba. "GShC-Net: Hybrid deep learning with DCTLAP feature extraction for brain tumor detection." Computational biology and chemistry (2025): 108577.
15. Mutawa, A. M., et al. "Randomization-Driven hybrid deep learning for diabetic retinopathy Detection." IEEE access 13 (2025): 38901-38913.
16. Dutta, Suvajit, et al. "Classification of diabetic retinopathy images by using deep learning models." International Journal of Grid and Distributed Computing 11.1 (2018): 89-106.

How to cite this article: Putti Venkata Siva Teja, Duba Thrisha, Begum Faridha, Chennu Swetha, Garikimukku Pravallika, Kolli Dedeepya Krishna. Early diabetes prediction using hybrid deep learning on retinal images. *International Journal of Research and Review*. 2026; 13(3): 318-326. DOI: *10.52403/ijrr.20260337*

******