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A Two-Stage Neural Network Framework for Automated Diabetic Retinopathy Detection

Dr. G. Suresh

Assistant Professor, Department of Computer Science,
Government Arts College for Women, Salem - 636008, Tamil Nadu, India.
Email: suresh2023phd@gmail.com

Abstract

Diabetic Retinopathy (DR) is a serious complication of diabetes that affects the retina and can lead to vision impairment or blindness if not detected early. This condition can be diagnosed by analyzing retinal images captured using a fundus camera. With advancements in artificial intelligence, particularly in deep learning, Diabetic Neural Networks (DNNs) have emerged as a powerful tool in biomedical signal analysis. These networks not only model complex image features but also effectively classify retinal images as normal or indicative of diabetic retinopathy. The automatic and accurate detection of DR plays a crucial role in timely intervention and can significantly reduce the risk of vision loss among diabetic patients.

The primary objective of this research is to design a robust classifier system for the early diagnosis of diabetic retinopathy using predictive neural networks. The proposed system is tailored for large-scale patient screening, providing a scalable solution to meet the growing demand for automated DR detection. The classifier incorporates a two-stage neural network framework: Diabetic Neural Network Stage 1 and Stage 2, each responsible for progressively refining the detection and classification process. This layered approach enhances diagnostic accuracy and supports ophthalmologists in making informed clinical decisions during mass screening procedures.

Keywords

Diabetic Retinopathy, Retinal Image Analysis, Fundus Images, Deep Neural Network, Automated Diagnosis, Medical Image Classification

1. Introduction

Diabetic retinopathy remains one of the leading causes of vision impairment among working-age adults, driven by progressive retinal vascular and neural damage due to chronic hyperglycemia. Timely and accurate screening is paramount to prevent irreversible vision loss [1, 2]. Recent years have seen accelerated progress in the use of artificial intelligence (AI) for automated DR detection from retinal fundus images. A comprehensive meta-analysis of real-world screening studies reported pooled sensitivity and specificity exceeding 87% and 90%, respectively, highlighting strong diagnostic performance compared to human graders [3]. Complementing this, a systematic review focused on computational efficiency examined 84 state-of-the-art models, emphasizing the importance of low-latency architectures such as vision transformers for deployment in resource-constrained settings. Several recent studies have demonstrated novel engineering approaches to improve both accuracy and interpretability. For instance, Refat et al. [4] introduced VR-FuseNet, fusing heterogeneous fundus datasets preprocessed by SMOTE and CLAHE with dual backbone models (VGG19 and ResNet50V2) and explainable AI techniques, yielding 91.82% accuracy. Shakibania et al. [5] developed a Dual Branch Deep Learning Network using two pre-trained feature extractors fine-tuned on multi-center datasets, achieving binary classification accuracy of 98.5% and stage-grading quadratic-weighted kappa of 0.93.

The concept of multi-stage neural network frameworks has also been validated by the field. [6] A 2024 study on two-stage deep learning classification employed gradient weighted class activation mapping for fundus image screening, improving lesion localization and severity grading. In earlier work, Yang et al. [7] proposed a two-stage DCNN pipeline that combined local lesion detection with global grading, significantly improving performance through imbalanced weighting for lesion patches. Hybrid architectures that combine CNNs with sequential models are also promising. [8] A 2023 Frontiers in Medicine article reported a hybrid CNN-LSTM model for DR subtype classification, achieving 96.1% accuracy by capturing spatial and temporal dependencies in fundus image sequences. These cutting-edge studies motivate our proposed framework. We aim to build a two-stage predictive neural network classifier for automated screening of diabetic retinopathy using fundus images, combining lesion localization and refinement stages analogous to proven pipelines, while incorporating robustness, interpretability, and computational efficiency informed by [4] and [5]. The proposed system is tailored for high-throughput mass screening, intended to assist ophthalmologists in early detection and severity classification of DR, with reduced workload and improved diagnostic accuracy.

2. Literature Survey

Recent advancements in automated diabetic retinopathy (DR) detection have significantly benefited from the application of deep learning and vision-based AI frameworks. Lakshmi K.S.

and Sargunam B. [9] presented an effective approach for DR detection and classification using deep learning architectures. Their method emphasizes precision and robustness in distinguishing normal from DR-affected images. Sharma and Lalwani [10] proposed a multi-model deep net embedded with an Explainable AI (XAI) framework to segment and classify DR stages, improving clinical interpretability alongside high classification performance. Akram et al. [11] introduced a Bayesian-enhanced uncertainty-aware deep learning model to address model reliability and confidence estimation in DR detection. Lee et al. [12] applied Vision Transformers for interpretable classification of metabolic syndrome via retinal images, showing potential crossover applications in DR prediction due to shared visual biomarkers. Similarly, Diwakar [13] combined Convolutional Neural Networks (CNNs) with Vision Transformers for more accurate DR detection, demonstrating the advantage of hybrid deep models.

El Habib Daho et al. [14] proposed DISCOVER, a novel 2D multiview summarization of Optical Coherence Tomography Angiography (OCTA) to automate DR diagnosis. This framework improved both diagnostic speed and accuracy using advanced summarization techniques. Ling [15] developed DeepDR Plus, a model focused on predicting DR progression by analyzing retinal image sequences, emphasizing the temporal dimension of disease monitoring using deep learning. Das et al. [16] created a robust CNN-based framework called DRFEC for feature extraction and classification of DR, outperforming traditional methods in accuracy and computational efficiency. Lastly, Sebastian et al. [17] conducted a comprehensive survey of deep learning methods applied to DR classification, covering architectures, datasets, and challenges, and setting a benchmark for future research in this area. Collectively, these works highlight the growing maturity and diversity of AI-based solutions in DR detection, ranging from CNNs and Vision Transformers to uncertainty-aware models and multimodal approaches. They also emphasize the role of interpretability, predictive monitoring, and clinical applicability in enhancing diagnostic outcomes.

3. Proposed Methodology

The proposed pre-diagnostic framework is structured into five sequential stages, each playing a crucial role in the accurate detection of diabetic retinopathy. The figure 1 shows the block diagram of the proposed model.

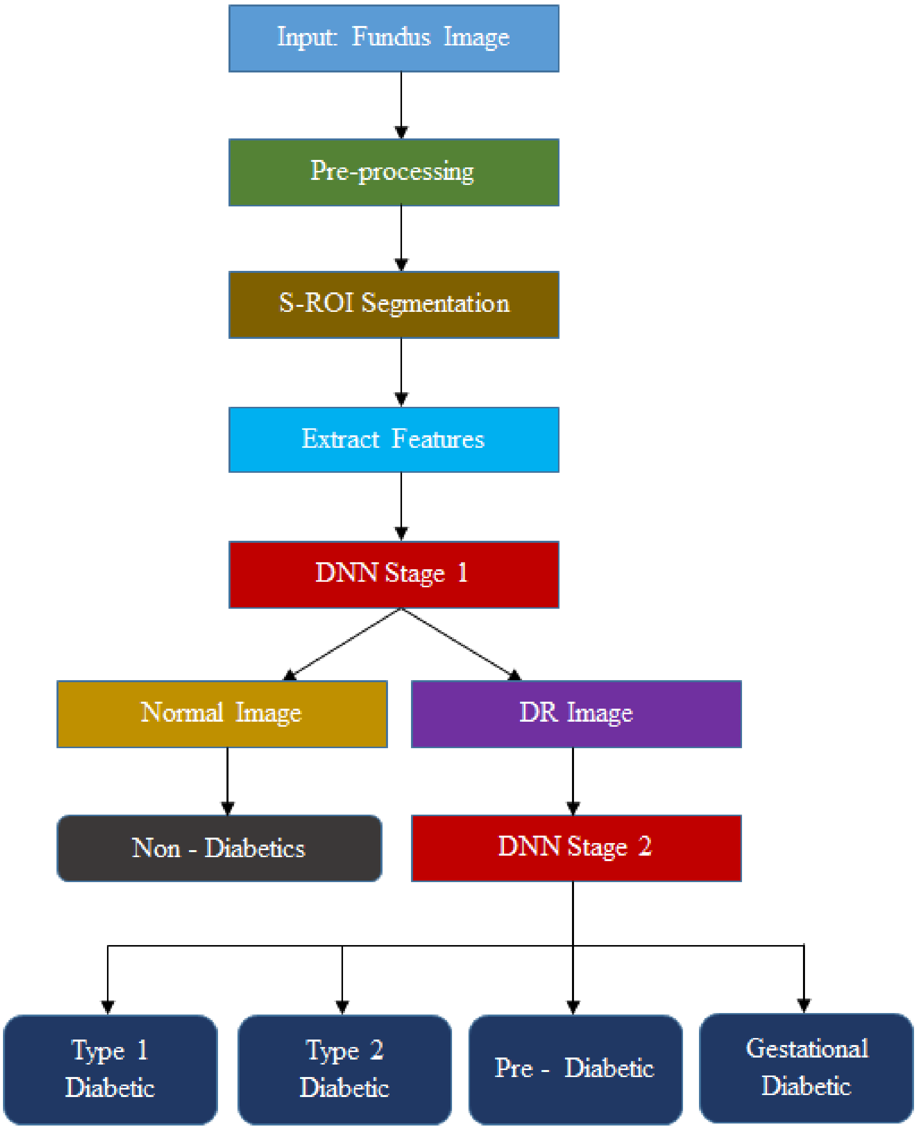

Figure 1. Architecture of proposed model

The stages are as follows:

- **Image Acquisition**: Retinal images are captured using a high-resolution fundus camera to ensure clear visualization of retinal features.
- **Image Pre-processing**: The acquired images undergo enhancement techniques to improve contrast, reduce noise, and standardize illumination, facilitating better feature extraction.
- **ROI Segmentation**: Key anatomical structures and pathological regions, such as blood vessels, microaneurysms, and exudates, are isolated using segmentation algorithms to focus the analysis on relevant regions.

- **Feature Extraction**: It is the process of identifying and quantifying key patterns or attributes from segmented retinal images that are most relevant for classification.
- **Image Classification**: A two-stage neural network model is applied to classify the segmented images into normal or various stages of diabetic retinopathy.

3.1 Image Acquisition

A well-curated collection of high-quality medical images, commonly referred to as a database, is essential for the effective evaluation and benchmarking of medical image processing algorithms. In the context of diabetic retinopathy detection, retinal image databases serve as standardized references, encompassing both normal and DR-affected retinal images. These images are meticulously verified and annotated by experienced ophthalmologists to ensure diagnostic reliability.

One such widely recognized resource is the MESSIDOR database, which provides a comprehensive set of eye fundus color images. These images were acquired across three ophthalmologic departments using a Topcon TRC NW6 non-mydriatic retinograph equipped with a color video 3CCD camera. Each image captures the retina with a 45-degree field of view, ensuring sufficient coverage for clinical analysis and automated diagnostic processing. The MESSIDOR database plays a pivotal role in developing and validating algorithms for the automated detection and classification of diabetic retinopathy.

3.2 Image Pre-processing

Image pre-processing plays a vital role in enhancing the quality and interpretability of retinal images before they are subjected to segmentation and classification tasks. In the context of diabetic retinopathy detection, the primary objective of pre-processing is to standardize the image appearance, suppress noise, and highlight important anatomical features such as microaneurysms, blood vessels, and exudates. This stage involves a sequence of steps, including grayscale conversion, image de-noising using Gaussian filtering, and contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE).

3.2.1 Grayscale Conversion

Color retinal images acquired from fundus cameras are typically in RGB format. However, for many processing tasks, especially when focusing on intensity-based features, it is beneficial to convert the image into grayscale. Grayscale conversion simplifies the image data by reducing the number of channels from three to one, making subsequent processing more efficient while preserving essential structural information.

The grayscale value $I_g(x, y)$ at pixel location (x, y) is computed using a weighted sum of the Red, Green, and Blue channels, as defined by:

$$I_g(x, y) = 0.2989 \cdot R(x, y) + 0.5870 \cdot G(x, y) + 0.1140 \cdot B(x, y) \quad (1)$$

Here, $R(x, y)$, $G(x, y)$ and $B(x, y)$ denote the red, green, and blue intensity values at pixel (x, y), respectively. The green channel is given more weight because it contains most of the luminance information in retinal images, especially for detecting fine vascular structures.

3.2.2 De-noising Using Gaussian Filter

Medical images are often contaminated with various types of noise during acquisition due to sensor imperfections, low lighting, or compression artifacts. In retinal imaging, Gaussian filtering is commonly used to remove high-frequency noise while preserving edges and overall image structure.

The Gaussian filter is a linear smoothing filter where the kernel is defined by a two-dimensional Gaussian function:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \cdot e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

Where, (x, y) are the pixel coordinates relative to the center of the kernel, σ is the standard deviation, which controls the amount of smoothing.

The filtered image $I_f(x, y)$ is obtained by the convolution of the grayscale image $I_g(x, y)$ with the Gaussian kernel $G(x, y)$:

$$I_f(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{j} I_g(x - i, y - j) \cdot G(i, j) \quad (3)$$

Here, k defines the window size. Gaussian filtering effectively suppresses background noise and improves the visibility of small structures like microaneurysms, which are important for early detection of diabetic retinopathy.

3.2.3 Contrast Enhancement Using CLAHE

Retinal images often suffer from uneven illumination and poor contrast, which can hinder the performance of segmentation and classification algorithms. To address this, CLAHE is used to enhance local contrast in the image.

a. Adaptive Histogram Equalization (AHE)

In AHE, the image is divided into non-overlapping regions called tiles. Histogram equalization is then applied independently to each tile to redistribute intensity values and improve local contrast. However, AHE can over-amplify noise in homogeneous regions.

b. CLAHE Enhancement

To overcome this, CLAHE introduces a contrast limiting step. The histogram is clipped at a predefined threshold (clip limit), and excess histogram bins are redistributed uniformly across all histogram bins before computing the cumulative distribution function (CDF). The CLAHE process involves:

Step1: Compute histogram $H(i)$ for each tile T, where i is the intensity level.

Step2: Clip histogram at the threshold H_c:

$$H_{clipped}(i) = \min\left(H(i), H_c\right) \tag{4}$$

Step3: Redistribute excess $E = \sum_i (H(i) - H_c)$ evenly across all bins.

Step4: Normalize the modified histogram to obtain the CDF $C(i)$.

Step5: Map original intensities $I(x, y)$ using:

$$I_{CLAHE}(x, y) = C(I_f(x, y) \times (L - 1) \tag{5}$$

Where, L is the number of gray levels, $I_f(x, y)$ is the smoothed grayscale pixel value from the Gaussian filter. Finally, the enhanced tiles are stitched together using bilinear interpolation to reduce boundary artifacts, producing the final contrast-enhanced image. These pre-processing techniques together produce a refined image suitable for high-accuracy segmentation and classification in the diabetic retinopathy detection pipeline.

3.3 ROI Segmentation

Statistical Region of Interest (S-ROI) is a widely used technique in medical image processing for identifying and isolating meaningful structures, such as blood vessels, lesions, or other anatomical features, within an image. Its primary function is to locate objects and boundaries including lines, curves, or regions—based on statistical characteristics and visual consistency. S-ROI segmentation facilitates precise delineation of retinal structures, ensuring that further analysis focuses on diagnostically relevant areas rather than extraneous background information.

In Statistical-ROI segmentation, pixel classification relies on statistical similarity across local neighborhoods. Common features include mean intensity μ, standard deviation σ, or entropy H. For a given local window $W(x, y)$ centered at pixel (x, y), the local mean μ and variance σ^2 are calculated as:

$$\mu(x, y) = \frac{1}{|W|} \sum_{(i,j)\epsilon W(x,y)} I(i, j) \tag{6}$$

$$\sigma^2(x, y) = \frac{1}{|W|} \sum_{(i,j)\epsilon W(x,y)} [I(i, j) - \mu(x, y)]^2 \tag{7}$$

Here, $I(i, j)$ is the pixel intensity and $|W|$ denotes the number of pixels in the window. Regions with similar statistical metrics are grouped into one segment, while regions with significant variation are separated.

In retinal images, background information such as non-retinal borders or illumination artifacts can vary significantly and often leads to reduced classification accuracy. Since the position and structure of retinal blood vessels differ between individuals and across image captures, including background areas in the analysis may introduce statistical noise and false patterns. To overcome this, segmentation through S-ROI is applied to isolate the retinal field and discard irrelevant background regions. This step is essential before feature extraction and classification, as it ensures that the algorithm focuses solely on regions containing diagnostic content. If $I(x, y)$ is the original image, and $M(x, y)$ is a binary segmentation mask such that:

$$M(x,y) = \begin{cases} 1, & if\ (x,y) \epsilon ROI \\ 0, & otherwise \end{cases} \tag{8}$$

Then the segmented image $I_s(x,y)$ is given by:

$$I_s(x,y) = I(x,y) \cdot M(x,y) \tag{9}$$

This multiplication operation zeroes out all background pixels, retaining only the statistically significant region of interest. The segmented image I_s can now be used for accurate feature extraction, classification, and database matching, free from background interference. This refined S-ROI segmentation framework significantly improves detection performance in diabetic retinopathy screening systems by ensuring precise localization and analysis of retinal structures.

3.4 Feature Extraction

In this stage of the pipeline, feature extraction is carried out on the pre-processed fundus images to identify clinically significant structures. The extracted features are categorized into four key components: the optic disc, fovea, vascular structure, and exudates, each of which plays a vital role in the diagnosis and grading of diabetic retinopathy.

3.4.1 Optic Disc Region Localization

The localization of the optic disc was initially performed by applying a thresholding technique to the red channel of the retinal image, as the optic disc typically appears brighter than surrounding regions in this channel. To refine the selection, the area-to-perimeter (edge) ratio of each candidate region was calculated, and the region with the highest ratio was identified as the most probable optic disc location due to its typically circular and compact shape. Subsequently, morphological closing operations were applied to eliminate small gaps and smooth the region boundaries. Finally, a convex hull-based approach was employed to accurately enclose the optic disc region, completing its localization with improved precision.

3.4.2 Fovea and Macula Localization

To accurately locate the fovea and macula, a combination of image subtraction and object segmentation techniques was employed. These methods help in isolating regions of interest by removing background interference and enhancing contrast between anatomical features.

Following this, morphological erosion was applied to refine the segmented regions, eliminating small artifacts and ensuring clearer boundary definition of the fovea and macula structures.

Anatomically, the fovea is typically located at a specific distance from the optic disc. In this model, the position of the fovea was estimated based on the known spatial relationship: it lies approximately 2 optic disc diameters away in the horizontal direction from the center of the optic disc. This geometrical constraint aids in robust and anatomically consistent localization across varying retinal images.

3.4.3 Retinal Blood Vessel Extraction

Retinal blood vessels were most effectively detected using the green channel of the fundus image, as it provides the highest contrast between the vessels and the surrounding retinal tissue. To enhance vessel visibility and suppress noise, the image underwent morphological reconstruction, which preserves important vessel structures while eliminating irrelevant background features.

Further enhancement was achieved through bottom-hat filtering, which emphasizes dark structures on a bright background ideal for highlighting blood vessels. The final segmented vessel map was produced by combining all reconstructed outputs, resulting in a refined and continuous representation of the vascular network essential for diabetic retinopathy analysis.

3.4.4 Exudate Detection and Feature Extraction

Exudates are one of the primary clinical indicators of diabetic retinopathy, characterized by yellowish-white spots in the retina. These lesions are formed due to lipid and protein leakage from damaged blood vessels and often appear within the temporal vascular arcades, occasionally exhibiting a distinct circular pattern with well-defined edges. Their presence and distribution are critical for disease grading and diagnosis.

To accurately identify exudates, features are extracted at the pixel level, considering parameters such as intensity, hue, mean brightness, standard deviation, and spatial location of the yellowish regions. Due to their distinctive appearance, the proposed detection method has demonstrated a high level of accuracy in identifying exudates compared to other retinal abnormalities such as microaneurysms or hemorrhages.

3.5 Image Classification

In this phase, the proposed framework implements a Diabetic Neural Network (DNN), structured as a two-stage architecture comprising DNN Stage 1 and DNN Stage 2. These sequential stages are designed to collaboratively improve the accuracy and reliability of diabetic retinopathy classification. The detailed working mechanism of the classification model is described in the following section.

3.5.1 DNN Stage 1

The number of neurons in the input layer is configured to match the total number of pixels in the input retinal image, ensuring complete data representation. Within the DNN, each convolutional layer extracts meaningful features by computing the dot product between learnable filters and localized image patches. These layers capture a variety of low- to mid-level visual attributes such as edges, contrast variations, blobs, and geometric shapes that are crucial for identifying diabetic retinopathy-related abnormalities. The final convolutional layer positioned just before the fully connected layers encapsulates the most informative and abstract features derived from earlier layers. A pooling layer is employed as the final operation in DNN Stage 2 to reduce spatial dimensions and improve generalization by down-sampling the feature maps.

The output layer of the model performs binary classification, categorizing each input image as either normal (without signs of diabetic retinopathy) or abnormal (with signs of diabetic retinopathy). In the proposed method, a two-layer DNN architecture was implemented, trained on a dataset of 1,000 retinal fundus images, and evaluated on an independent test set comprising 200 images. This architecture provides an effective balance between model complexity and diagnostic performance.

3.5.2 DNN Stage 2

The primary application of the DNN lies in the automated recognition and analysis of retinal fundus images for the detection of diabetic retinopathy. Unlike traditional feed-forward neural networks, which are often inadequate for handling time-series or sequential data such as stock market trends or video streams the proposed DNN architecture incorporates a hybrid structure designed to process both spatial and sequential patterns effectively. To enhance diagnostic precision, the model integrates DNN Stage 2 networks with each DNN Stage 1 network, enabling a deeper and more contextual understanding of the input data. This layered approach is particularly useful in interpreting progressive and time-dependent features in retinal images, allowing the system to infer specific types or stages of diabetic retinopathy based on temporal or weighted feature representations.

The performance of the model is rigorously evaluated using a comprehensive set of image quality and similarity metrics, including:

- Mean Squared Error (MSE): Measures average squared difference between predicted and actual values.
- Peak Signal-to-Noise Ratio (PSNR): Evaluates reconstruction quality relative to noise.
- Normalized Cross-Correlation (NCC): Assesses similarity between two images.
- Maximum Difference (MD) and Average Difference (AD): Indicate deviation between predicted and original image intensities.
- Structural Content (SC) and Structural Similarity Index (SSIM): Quantify structural fidelity of the image.
- Normalized Absolute Error (NAE): Measures the normalized absolute pixel-wise error.

These metrics collectively validate the model's accuracy, structural integrity, and robustness in DR classification tasks.

4. Results and Discussion

In this research, we utilized a publicly available and widely recognized dataset specifically designed for benchmarking diabetic retinopathy detection in digital fundus images: the DIARETDB1 database. This standard diabetic retinopathy dataset comprises 25 high-resolution color fundus images, which have been meticulously annotated and categorized by a panel of expert ophthalmologists. The images are manually labeled as either normal (without signs of diabetic retinopathy) or abnormal (exhibiting features indicative of diabetic retinopathy), ensuring a high level of diagnostic reliability.

To support training and classification across different stages of the disease, the dataset used in this study was expanded to include a custom training set of 1,000 fundus images, distributed across five clinically relevant categories: Type 1 Diabetic, Type 2 Diabetic, Pre-Diabetic, Gestational Diabetic, and No-Diabetic. These classes reflect the varying levels of diabetic progression and risk, providing a comprehensive foundation for developing and evaluating the proposed two-stage neural network model. The severity levels of diabetic retinopathy, typically categorized into four main stages, are illustrated in Figure 2, offering a visual guide to the classification objectives of the system.

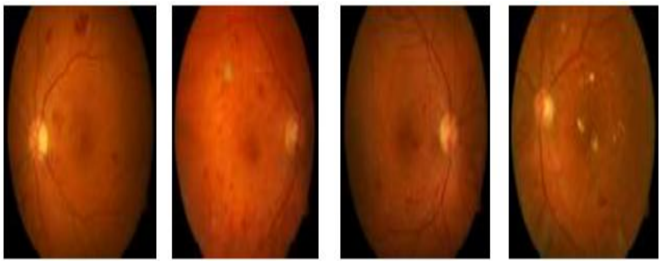

Figure 2. Sample images

In the proposed methodology, a series of specialized algorithms have been employed at each stage of the pipeline to enhance the overall performance of diabetic retinopathy detection. These stages include image pre-processing, segmentation, feature extraction, and classification, each optimized to deliver high accuracy, sensitivity, and specificity in identifying retinal abnormalities. To ensure reliable and consistent outcomes, the system integrates tailored techniques at each level that collectively improve the precision of both classification and lesion localization. Enhancing sensitivity ensures better detection of true positive cases, while improved specificity reduces false positives both of which are critical for clinical applications.

To facilitate the evaluation of the proposed two-stage neural network model, a Graphical User Interface (GUI) has been developed. This user-friendly interface allows for visual analysis and performance assessment of each processing stage. The results and performance metrics generated through this interface are presented in Figures 3 and 4, demonstrating the model's effectiveness across different image categories and disease severity levels.

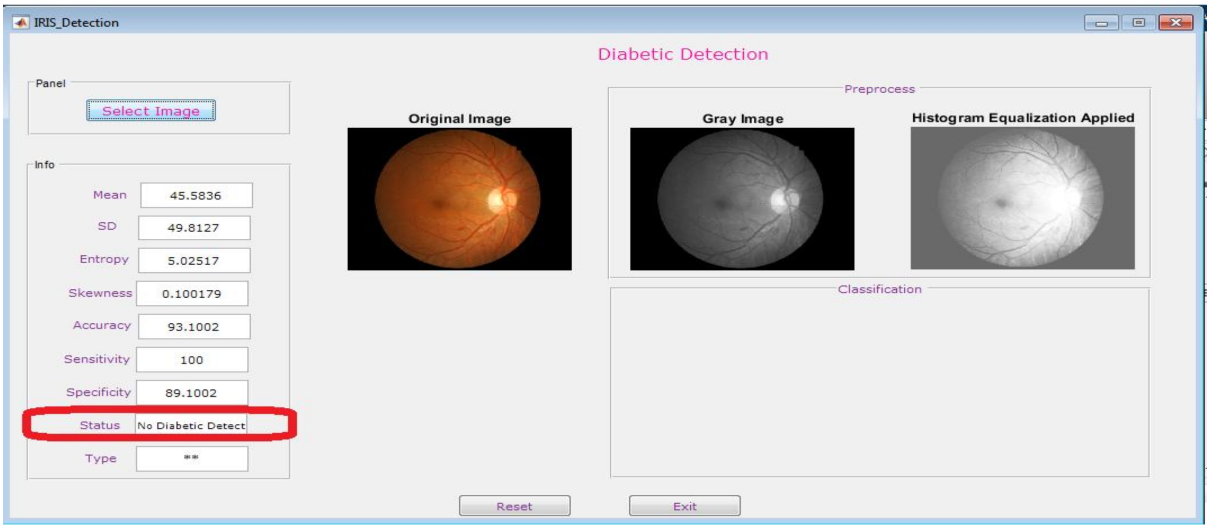

Figure 3. The result shows the classified output is No-Diabetic

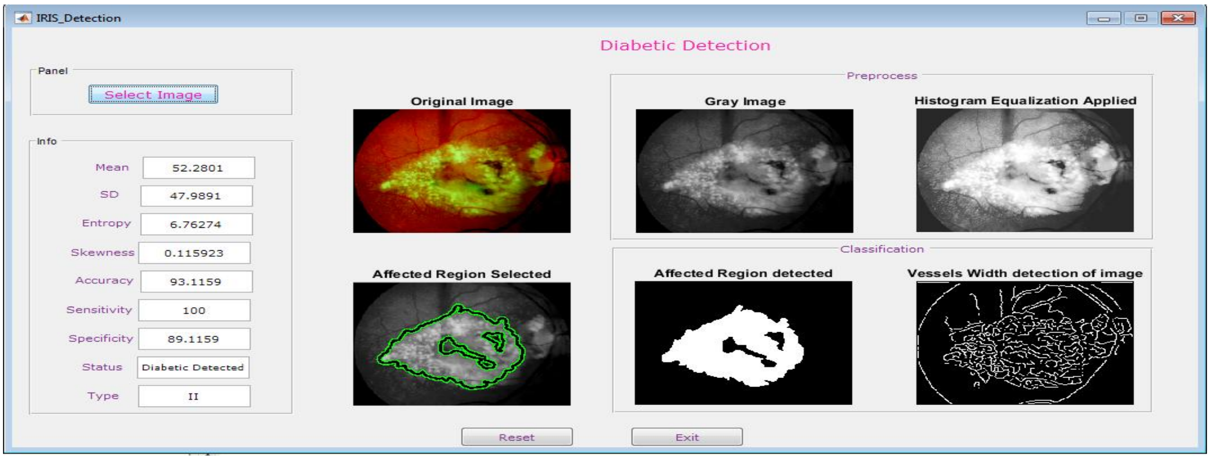

Figure 4. The result shows the classified output is Type-II Diabetic

To validate the effectiveness of the proposed model, a comparative analysis was conducted against widely used existing deep learning techniques, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The performance metrics obtained from these models were benchmarked against those of the proposed two-stage Diabetic Neural Network framework. The comparative results highlighting improvements in classification accuracy, sensitivity, and specificity are comprehensively presented in Table 1 and visually illustrated in Figure 5, clearly demonstrating the superior performance of the proposed method.

Table 1 Comparison of proposed model with existing techniques

Method	**Sensitivity**	**Specificity**	**Accuracy**

DNN	99.0	96.0	98.5
CNN	98.0	95.0	97.6
RNN	90.0	88.0	89.6

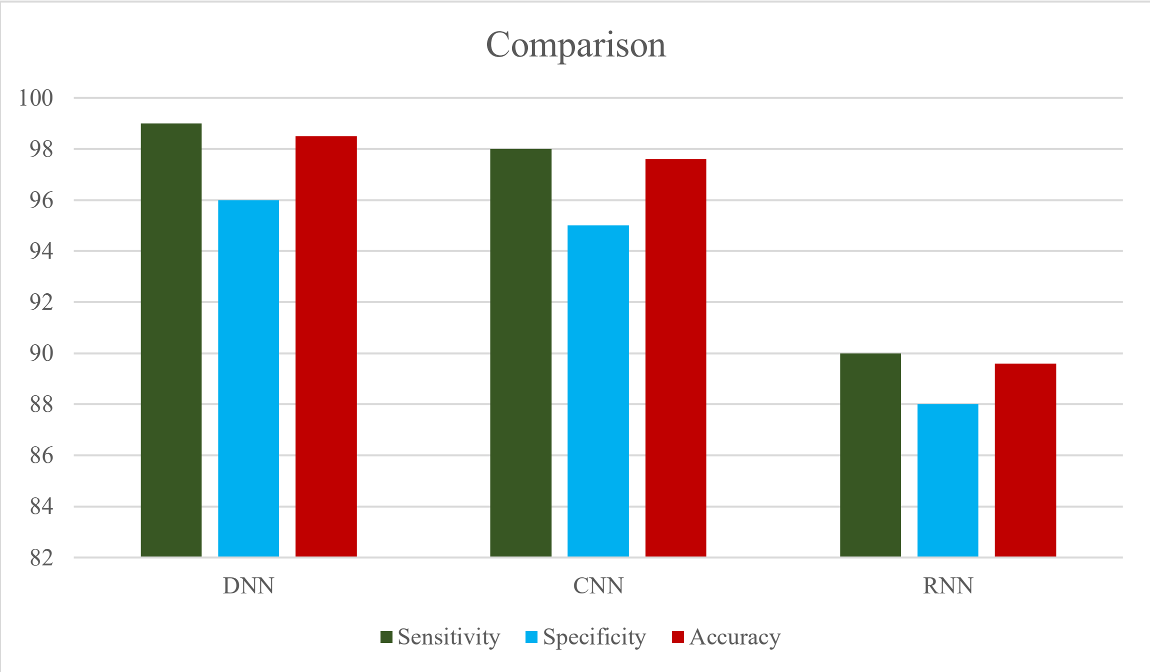

Figure 5. Comparison with existing techniques

5. Conclusion

Diabetic Retinopathy (DR) is a serious complication of Diabetes Mellitus (DM), primarily caused by damage to the blood vessels in the retina—the light-sensitive layer at the back of the eye. In its early stages, DR often presents without noticeable symptoms, resulting in subtle vision issues. However, if left undetected and untreated, it can progress to severe stages, ultimately leading to irreversible blindness. Early detection is therefore crucial for effective treatment and vision preservation. To address this, the proposed study leverages Deep Neural Network technology as a powerful diagnostic aid for DR screening. Acting as a virtual assistant to ophthalmologists, the DNN enhances diagnostic accuracy and speeds up mass screening processes. In this research, three types of neural networks were evaluated: CNN, RNN, and Diabetic Neural Networks (DNN). Among them, the DNN demonstrated superior performance, achieving an accuracy of 98.5%, compared to 97.6% with CNN and 89.6% with RNN.

Looking ahead, this framework can be extended beyond retinal analysis. According to the World Health Organization (WHO), diabetic complications often lead to multi-organ damage, with the lungs being among the most affected. As a future enhancement, this model can be adapted to detect pulmonary complications in diabetic patients by replacing the current Statistical-Region of Interest (S-ROI) segmentation process with one tailored for lung image analysis—thus broadening its diagnostic capabilities and clinical impact.

6. References

1. Rahim Refat S., Raha Z.S., Sarker S., Preotee F.F., Rahman M.M., Muhammad T., Islam M.S., "VR-FuseNet: A Fusion of Heterogeneous Fundus Data and Explainable Deep Network for Diabetic Retinopathy Classification", *arXiv preprint,* 2025.
2. Shakibania H., Raoufi S., Pourafkham B., Khotanlou H., Mansoorizadeh M., "Dual Branch Deep Learning Network for Detection and Stage Grading of Diabetic Retinopathy", *Biomed Signal Process Control*, 93, 106168, 2024.
3. Nazeef Ul Haq, Talha Waheed, Kashif Ishaq, Muhammad Awais Hassan, Nurhizam Safie, Nur Fazidah Elias & Muhammad Shoaib, "Computationally efficient deep learning models for diabetic retinopathy detection: a systematic literature review", *Artificial Intelligence Review*, Vol. 57, No. 1, pp. 309, 2024.
4. Abdullah S Alqahtani, Wasan M Alshareef, Hanan T Aljadani, Wesal O Hawsawi, Marya H Shaheen, "The efficacy of artificial intelligence in diabetic retinopathy screening: a systematic review and meta-analysis" *International Journal of Retina and Vitreous*, 11, No. 1, pp. 214, 2025.
5. Dai L., Sheng B., Chen T., et al. "A deep learning system for predicting time to progression of diabetic retinopathy." *Nature Medicine*, 30(5), pp. 584–594, 2024.
6. Abderaouf M. Moustari,Youcef BrikORCID Icon,Bilal Attallah &Rafik Bouaouina, "Two-stage deep learning classification for diabetic retinopathy using gradient weighted class activation mapping" *Annals of Ophthalmology Journal,* 2024.
7. Yang Y., Li T., Li W., Wu H., Fan W., Zhang W. Lesion detection and grading of diabetic retinopathy via two-stages deep convolutional neural networks. *arXiv preprint*, 2017.
8. Aristidou A., Jena R., Topol E.J., "A hybrid CNN-LSTM model for diabetic retinopathy subtype classification", *Frontiers in Medicine, Vol. 7(1), pp. 518-536,* 2023.
9. Lakshmi K.S., Sargunam B., "Using Deep Learning Architectures for Detection and Classification of Diabetic Retinopathy", *International Ophthalmology*, 44(1), pp. 90–102, 2024.

10. Sharma N., Lalwani P., "A Multi-Model Deep Net with Explainable AI Framework for Diabetic Retinopathy Segmentation and Classification", *Scientific Reports*, 15(1), pp. 8777–8789, 2025.
11. Akram M., Adnan M., Ali S.F., "Uncertainty-Aware Diabetic Retinopathy Detection Using Deep Learning Enhanced by Bayesian Approaches", *Scientific Reports*, 15(1), pp. 1342–1356, 2025.
12. Lee T.K., Kim S.Y., Choi H.J., "Vision Transformer-Based Interpretable Metabolic Syndrome Classification Using Retinal Images", *NPJ Digital Medicine*, 8(1), pp. 205–217, 2025.
13. Diwakar M., "Diabetic Retinopathy Detection and Analysis with Convolutional Neural Networks and Vision Transformer", *Biomedical Informatics and Smart Healthcare*, 1(1), pp. 18–26, 2025.
14. El Habib Daho M., Li Y., Zeghlache R., "DISCOVER: 2-D Multiview Summarization of Optical Coherence Tomography Angiography for Automatic Diabetic Retinopathy Diagnosis", *arXiv preprint,* 2024.
15. Ling M., "DeepDR Plus: Predicting Diabetic Retinopathy Progression from Retinal Image Sequences Using Deep Learning", *International Journal of Retina and Vitreous*, vol. 2(1), pp. 341, 2024.
16. Das D., Biswas S.K., Bandyopadhyay S., "Detection of Diabetic Retinopathy Using Convolutional Neural Networks for Feature Extraction and Classification (DRFEC)", *Multimedia Tools and Applications*, vol. 1(1), pp. 118-135, 2022.
17. Sebastian A., Elharrouss O., Al-Maadeed S., Almaadeed N., "A Survey on Deep-Learning-Based Diabetic Retinopathy Classification", *Diagnostics*, 13(3), pp. 345–360, 2023.