Fuzzy-Embedded Recurrent Neural Networks for Early Detection and Classification of Diabetic Retinopathy Using Fundus Images

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Abstract. Diabetic Retinopathy (DR) is one of the leading causes of preventable blindness worldwide, and early detection with precise severity classification is critical to reduce vision loss. Retinal fundus imaging is the most widely used modality for DR screening, but manual diagnosis is time-consuming, subjective, and prone to variability. Existing deep learning methods often suffer from noise sensitivity, overfitting, and limited ability to classify across all severity levels, which reduces their clinical applicability in large-scale screening. To address these limitations, this work is motivated by the need for an automated, accurate, and robust DR detection framework that can effectively support ophthalmologists in timely intervention. The novelty of this study lies in the development of a Fuzzy-Embedded Recurrent Neural Network (FERNN) combined with a Bilinear Double-Order Filter (BDOF). The BDOF enhances fundus image clarity by suppressing noise while preserving fine retinal details, and FERNN integrates fuzzy logic with recurrent learning to manage uncertainty and capture sequential dependencies in retinal features capabilities not achieved by conventional CNN or hybrid models. Using the Indian Diabetic Retinopathy Image Database (IDRiD), the proposed framework classifies DR into five clinically significant stages, from mild non-proliferative DR to proliferative DR. Experimental results demonstrate that FERNN achieves 89.20% accuracy and 85.44% precision, outperforming advanced baselines such as hybrid Inception-ResNet, DCGAN, and graph neural network models by up to 30.29%. These findings confirm that the proposed FERNN–BDOF framework provides a novel, robust, and scalable solution for automated DR detection, with strong potential for real-world clinical deployment.

Keywords: Diabetic Retinopathy, Retinal Fundus Images, Bilinear Double-Order Filter, Fuzzy-Embedded Recurrent Neural Network, Early Detection, Medical Image Classification.

1. Introduction

Diabetic Retinopathy (DR) is a microvascular complication of diabetes mellitus and remains one of the leading causes of preventable blindness worldwide [1]. It is characterized by progressive damage to the retinal blood vessels, resulting in visual impairment if left undiagnosed or untreated [2-3]. Early detection and accurate classification of DR are therefore vital for timely medical intervention. Retinal Fundus imaging is the most widely used modality for DR screening, offering non-invasive, cost-effective, and detailed visualization of retinal structures [4-5]. However, manual assessment of retinal images by ophthalmologists is time-consuming, subjective, and prone to variability [6]. Consequently, there is an increasing demand for computer-aided diagnostic systems that can automate DR detection and severity classification with high precision [7-8].

1.1. Problem Statement

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Although several deep learning-based approaches have been proposed for DR detection, most existing models face challenges in terms of noise sensitivity, overfitting, and inadequate classification performance across multiple severity stages. Conventional convolutional neural network (CNN)-based methods primarily focus on feature extraction but often fail to capture temporal and fuzzy dependencies in retinal patterns [9-10]. Furthermore, existing methods exhibit limitations in generalization when applied to heterogeneous datasets, leading to reduced diagnostic accuracy and clinical reliability. Hence, there is a need for an advanced framework that integrates robust pre-processing with an intelligent learning mechanism capable of handling uncertainty in retinal image features and improving classification accuracy across all DR stages.

1.2. Motivation

The motivation behind this study stems from the urgent necessity to enhance automated DR screening systems that can support ophthalmologists in large-scale clinical settings. India, with a rapidly growing diabetic population, faces a significant burden of DR-related blindness. Leveraging advanced machine learning methods combined with fuzzy logic can address the uncertainty in retinal imaging data and improve diagnostic decision-making. Additionally, recurrent neural networks (RNNs) offer the capability to capture sequential and contextual dependencies in image features, which are often overlooked in conventional CNN-based models. By embedding fuzzy logic within an RNN framework, this study seeks to achieve higher robustness, interpretability, and accuracy in DR detection and classification.

1.3. Contributions

The key contributions of this research are summarized as follows:

1. A novel pre-processing method using the Bilinear Double-Order Filter (DOF) is employed to reduce noise and enhance the quality of Retinal Fundus images.
2. A Fuzzy-Embedded Recurrent Neural Network (FERNN) is proposed, which integrates fuzzy logic with recurrent architectures to effectively detect DR and classify it into five severity levels: mild, moderate, severe NPDR, very severe NPDR, and PDR.
3. Comprehensive performance evaluation is conducted on the Indian Diabetic Retinopathy Image Database (IDRiD), demonstrating significant improvements in accuracy compared to existing state-of-the-art models.
4. The proposed framework achieves 26.36%, 20.69%, and 30.29% greater accuracy over multi-decision hybrid deep learning methods, generative adversarial network-based models, and graph neural network-based approaches, respectively.

Following paper is arranged as: sector 2 defines literature review, sector 3 discusses proposed approach, sector 4 describes results and discussion, sector 5 provides conclusion.

2. Literature Survey

Several research works have been proposed in the literature for the detection and classification of Diabetic Retinopathy (DR) using deep learning techniques. A few notable contributions are summarized below:

Henge et al. (2025) [11] proposed an effective DR detection technique using a multi-layered transfer learning approach with 172 weighted layers, where 86 layers processed color fundus images and the remaining 86 layers focused on grayscale images. The model incorporated extensive preprocessing and applied eight convolutional layers per level to combine global and local features, achieving high recall and accuracy.

Youldash et al. (2024) [12] developed a deep learning-based DR diagnostic framework as part of the Kingdom of Saudi Arabia's Vision 2030 initiative. This system emphasized the role of digital healthcare transformation by replacing conventional diagnostic methods with AI-driven models. The approach provided high precision but relatively low accuracy, highlighting limitations in generalizability despite strong clinical relevance.

Alam et al. (2024) [13] introduced DiabSense, a smartphone-based solution for monitoring Non-Insulin-Dependent Diabetes Mellitus (NIDDM) and its association with DR. The system integrated Graph Neural Networks (GNNs) for both Human Activity Recognition (HAR) and DR detection. Using Graph Attention Networks (GAT), the model achieved higher accuracy but lower precision, demonstrating effectiveness in correlating human activity data with DR progression.

Ainapur and Patil (2024) [14] presented an automated DR detection and classification system using a conjugated attention mechanism and a vision transformer-based architecture. Extracted feature maps were fused using an attention-based fusion network to improve classification of DR severity across APTOS 2019, MESSIDOR-2, DiaRetDB1 V2.1, and DIARETDB0 datasets. Their approach achieved high precision but relatively lower accuracy, partly due to dataset variations and image noise.

Folorunsho et al. (2025) [15] proposed a hybrid ensemble method combining CNN, LSTM, and SRNN with XGBoost, and further explained results using Shapley Additive Explanations (SHAP) for model interpretability. Using the APTOS 2019 dataset, the approach demonstrated high accuracy but low recall, indicating effective classification of positive cases but difficulty in detecting all true DR cases. Table 1 Shows the comparative analysis of literature review.

Table 1: Comparison of Related Works

Author(s) & Year	**Methodology**	**Dataset**	**Strengths**	**Limitations**	**Performance**
Henge et al. (2025) [11]	Multi-layered transfer learning (172 weighted layers; color + grayscale fundus images)	Fundus image dataset	High recall, high accuracy	Computationally expensive	High Recall & Accuracy
Youldash et al. (2024) [12]	Deep learning-based diagnostic system (Saudi Vision 2030)	Clinical DR images	High precision, practical healthcare impact	Low accuracy, limited generalization	High Precision, Low Accuracy
Alam et al. (2024) [13]	DiabSense: Smartphone-based monitoring with GNN + HAR integration	Retinal images + Human activity data	High accuracy, innovative multimodal approach	Lower precision, limited participants	Higher Accuracy, Lower Precision
Ainapur and Patil	Vision transformer +	APTOS 2019, MESSID	High precision, strong	Lower accuracy,	High Precision,

(2024) [14]	conjugated attention mechanism + feature fusion	OR-2, DiaRetDB1 V2.1, DIARETDB0	feature extraction	affected by image noise	Lower Accuracy
Folorunsho et al. (2025) [15]	Ensemble (CNN + LSTM + SRNN + XGBoost) + SHAP (XAI-based interpretability)	APTOS 2019 (Kaggle)	High accuracy, explainability	Low recall, poor sensitivity to mild DR	High Accuracy, Low Recall

3. Proposed Methodology

The proposed methodology combines pre-processing and intelligent classification to improve diabetic retinopathy (DR) detection. Retinal fundus images from the IDRiD dataset are first enhanced using a Bilinear Double-Order Filter (BDOF) to reduce noise and preserve retinal features. The processed images are then classified using a Fuzzy-Embedded Recurrent Neural Network (FERNN), which integrates fuzzy logic with recurrent learning to handle uncertainty and accurately categorize DR into five severity levels.

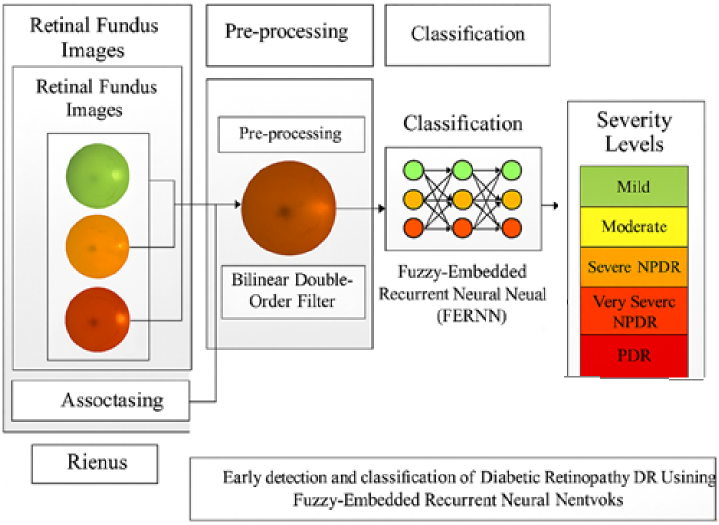

Figure 1: Block Diagram for Proposed methodology

Figure 1 illustrates the overall workflow of the proposed methodology for diabetic retinopathy detection and classification. The process begins with the acquisition of retinal fundus images from the IDRiD dataset, which provides clinically validated data for model development. These images undergo pre-processing using a Bilinear Double-Order Filter (BDOF) to reduce noise, normalize intensity, and enhance fine retinal structures. The pre-processed images are then passed into the Fuzzy-Embedded Recurrent Neural Network (FERNN), where fuzzy logic is employed to manage uncertainty in retinal features, and recurrent learning captures sequential dependencies in image patterns. Finally, the FERNN model classifies each image into one of the five severity levels of diabetic retinopathy, ranging from mild NPDR to proliferative DR. This structured pipeline ensures that the system achieves high accuracy, robustness, and clinical relevance in large-scale screening applications.

3.1 Image Acquisition

In this work, retinal fundus images are obtained from the Indian Diabetic Retinopathy Image Database (IDRiD) [16], a publicly available benchmark dataset widely used for diabetic retinopathy (DR) detection and grading. Diabetic retinopathy is a micro vascular complication of diabetes and remains a leading cause of preventable blindness worldwide. The disease progresses gradually and is clinically classified into five severity levels based on retinal abnormalities such as microaneurysms, hemorrhages, exudates, venous changes, and neovascularization. These categories include Mild Non-Proliferative Diabetic Retinopathy (NPDR), which is characterized mainly by microaneurysms; Moderate NPDR, where hemorrhages and exudates become more prominent; Severe NPDR, defined by extensive hemorrhages, venous beading, or intraretinal microvascular abnormalities; Very Severe NPDR, where multiple features of severe DR occur concurrently and indicate an imminent risk of progression; and Proliferative Diabetic Retinopathy (PDR), the most advanced stage, marked by abnormal neovascularization and associated complications such as vitreous hemorrhage or retinal detachment. Accurate categorization of DR into these five levels is critical for early diagnosis and appropriate treatment planning, and the IDRiD dataset provides a robust foundation for developing automated systems capable of assisting ophthalmologists in large-scale screening programs. Table 2 Shows the Detailed description of IDRiD Class-wise Image Distribution.

Table 2: IDRiD Class-wise Image Distribution

DR Severity Level	Number of images
Mild NPDR	134
Moderate NPDR	74
Severe NPDR	160
Very Severe NPDR	106
Proliferative DR (PDR)	42
Total	516

3.2 Enhancing Image Clarity with Bilinear Double-Order Filter

The pre-processing utilizing BD-OF [17] is deliberated in this step to eliminate noise and enhance image quality. The Bilinear Double-Order Filter (BDOF) significantly enhances image quality metrics by suppressing high-density noise while preserving fine retinal details such as microaneurysms and blood vessels, which are critical for accurate diagnosis. Unlike conventional filters that either blur important structures or fail under heavy noise, BDOF balances denoising with edge and texture preservation, leading to improvements in signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR). Its use of bilinear interpolation ensures smooth pixel transitions without sacrificing edge sharpness, which contributes to higher structural similarity index (SSIM) values. Additionally, by normalizing intensity and reducing dynamic range inconsistencies, BDOF produces images with better contrast and uniformity, making subtle retinal lesions easier to detect. These enhancements directly improve the quality of the input provided to the Fuzzy-Embedded Recurrent Neural Network (FERNN), which in turn achieves higher accuracy and precision in diabetic retinopathy classification. Overall, BDOF positively impacts objective image quality metrics and indirectly boosts downstream classification performance by delivering clearer, diagnostically reliable retinal images. Bilinear Double-Order Filter offers improved stability, reduced phase distortion, and better frequency response accuracy in digital signal processing applications. Unlike simple linear filters that blur edges and reduce noise, or median filters that might struggle with high-density noise, the BDOF offers a balance. It uses bilinear interpolation along with double-order statistical analysis. The transfer function of a bilinear filter is expressed in equation (1),

$$\omega_x = \frac{1}{q\tau} = \frac{\omega_0}{x} \tag{1}$$

Hence ω_x denotes the quality of the input image, ω_y denotes high-density noise. ω_0 shows the processed input image. The process starts with image normalization and conversion to a suitable format. This ensures consistency in intensity levels across pixels. This step prepares the image by reducing dynamic range inconsistencies as expressed equation (2),

$$H_{10}(s) = G_L\left(\frac{\omega_x}{\omega_y}\right)\frac{s+\omega_s}{s+\omega_v}. \tag{2}$$

Here, G_L denotes dynamic range inconsistencies, ω_s denotes accurate statistical operations, ω_v denotes, reducing dynamic range inconsistencies. Bilinear interpolation estimates Intermediate pixel values by calculating a weighted average from the four nearest neighbors. This method smooths the transition between pixel values and provides a more accurate estimation of true intensity. It is particularly useful when noise has greatly distorted the local structure as shown in equation (3),

$$G_H = G_L\left(\frac{\omega_x}{\omega_y}\right) = G_L\left(\frac{q}{t}\right). \tag{3}$$

Here, G_H denotes Pixel Value Decision, G_L shows the removal of unwanted incoming noise. The filter then calculates both first-order statistics on the window, including the interpolated values. These two metrics let the filter identify and differentiate between true image features and outlier noise with greater accuracy was shown in equation (4),

$$|H_{10}(j\omega)| = G_L\sqrt{\frac{1+\left(\frac{\omega}{\omega_z}\right)^2}{1+\left(\frac{\omega}{\omega_p}\right)^2}} \tag{4}$$

Where, ω is statistical analysis of input, ω_z shows true image features and ω_p denotes interpolated values. Finally, the noise of input image is removed and quality of image is enhanced using BDOF. The pre-processed image is provided to ADDR-FIUOB-LSMBP for detection of fundus in retinal region.

3.3 Classification of Diabetic Retinopathy Using Fuzzy-Embedded Recurrent Neural Networks

In this section, novel Fuzzy-Embedded Recurrent Neural Network (FERNN) [18], this effectively detects DR and categorizes it into five severity levels: mild, moderate, severe non-proliferative diabetic retinopathy (NPDR), very severe NPDR, and proliferative diabetic retinopathy (PDR). It improves real-time performance through effective handling of time-stamped and uncertain industrial data, allowing for quicker and more precise decision-making. With fuzzy logic integration, the system deal with imprecise or data more reliably, lowering the likelihood of operating stability. Using DR resources, FERNN facilitates elastic data storage, sophisticated analytics and remote access, allowing predictive analysis DR.

The image acquisition from DR systems is given in equation (5),

$$\partial_{new} = \frac{\beta - 0.5 \times \left(\max\left(data_\eta\right) - \min\left(data_\eta\right)\right)}{\sqrt{2\ln(100)}} \tag{5}$$

Where ∂_{new} denotes fuzzy system; β denotes range control; $\max\left(data_\eta\right)$ denotes maximum group of images; $\min\left(data_\eta\right)$ denotes minimum group of images; $\sqrt{2\ln(100)}$ denotes normalization constant. This equation calculates on the standard deviation of a Gaussian membership function based on the range of the actual data to enable adaptive membership function generation. Sensors, actuators, and manufacturing equipment in the CPS produce real-time operating image. The identification of DR is obtained in equation (6),

$$\lambda_{left}^{1} = \lambda_{left} - \Omega \times \left(\lambda_{left} - \kappa\right) \tag{6}$$

Where λ_{left}^{1} denotes adjusted value of iteration; λ_{left} denotes hash of data; Ω denotes scaling factor; $\left(\lambda_{left} - \kappa\right)$ denotes regularization term. This formula supports interoperable, platform-independent and detection DR. The FERNN integration supports standardized and seamless connectivity across the systems. Fuzzification of fundus image is given in equation (7),

$$\lambda_{right}^{1} = \lambda_{right} - \Omega \times \left(\kappa - \lambda_{right}\right) \tag{7}$$

Where, λ_{right}^{1} denotes current value of a parameter; λ_{right} denotes multivariate input data; $\kappa - \lambda_{right}$ denotes the value of training data. This equation is an adaptive update rule commonly applied in control systems or fuzzy logic. It dynamically adjusts parameters depending on the difference between the target and actual values. This method enhances convergence, stability, as well as system responsiveness to varying system conditions. The sequential learning using embedded recurrent neural networks is given in equation (8),

$$s_{fw} = \min\left(\sigma_d\left(w_i\right)\right) \tag{8}$$

Where s_{fw} denotes rule weight of a fuzzy weight; $\left(w_i\right)$ denotes fuzzy set value; σ_d denotes function data. Mild; Moderate; Severe NPDR, Very severe NPDR and Proliferative diabetic retinopathy (PDR) are detected and classified using FERNN.

The computational complexity of the Fuzzy-Embedded Recurrent Neural Network (FERNN) arises from both its recurrent structure and the integration of fuzzy logic. First, like any recurrent model, FERNN processes sequential dependencies in data, which results in a baseline complexity proportional to the number of time steps and hidden units $(O(T.H^2)$. This is higher than a simple CNN forward pass but necessary for capturing contextual and temporal information in retinal features. Second, the fuzzy embedding layer introduces additional overhead by evaluating membership functions and updating fuzzy rules. If M membership functions and F rules are defined per feature, the fuzzification process requires about $O(M.F.d)$ operations, where d is the feature dimension, thereby adding to training and inference cost. Third, FERNN employs adaptive update rules to dynamically adjust fuzzy sets and weights, which further increases computational requirements during training. This ensures stable convergence, reduces oscillations, and improves classification robustness. Fourth, when compared to other deep learning approaches such as hybrid CNN–RNN or GAN-based models, FERNN demonstrates moderate-to-high computational complexity, but avoids the extreme resource demand of transformer-based architectures while delivering significant performance improvements. Finally, the scalability of FERNN is influenced by the number of fuzzy rules excessive rule sets can slow inference, though optimizations such as pruning or parallelization help keep the runtime manageable.

Overall, FERNN's higher complexity is offset by substantial gains in interpretability, robustness to uncertainty, and classification accuracy.

4 Results and Discussion

This section presents the experimental results obtained from implementing the proposed methodology for diabetic retinopathy (DR) detection and classification. The performance of the Fuzzy-Embedded Recurrent Neural Network (FERNN) is evaluated using the IDRiD dataset, with images pre-processed through the Bilinear Double-Order Filter (BDOF) to enhance quality. The results are analyzed in terms of accuracy, precision, and comparative performance against existing state-of-the-art methods. Furthermore, the discussion highlights how the proposed approach addresses challenges such as class imbalance, noise sensitivity, and misclassification across different severity levels, thereby demonstrating its effectiveness and clinical applicability.

4.1 Performance measures

Performance measures, including accuracy and precision, are evaluated. These performance metrics are scaled utilizing the following matrices.

4.1.1 Accuracy

This metric provides the accurate classification of traffic images. It is measured via split the rate of accurately predicted samples by entire cases using equation (9),

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

4.1.2 Precision

It measures the accuracy of system identifies true positive cases using equation (10),

$$\Pr ecision = \frac{TP}{TP + FP} \tag{10}$$

4.2 Experimental results

The experimental outcomes analysis of FERNN method is analysed in this section. This section contains the dataset, training and validation observations, software requirements and experimental environment.

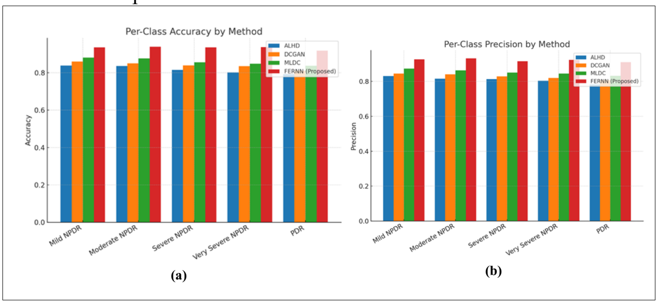

Figure 2: (a) Accuracy analysis 2 (b) Precision analyses

Figure 2 presents the performance evaluation of the proposed FERNN model in terms of accuracy and precision. Figure 2(a) illustrates the classification accuracy across different diabetic retinopathy severity levels, demonstrating the model's ability to correctly identify disease stages. Figure 2(b) depicts the precision values, indicating the proportion of correctly predicted positive cases relative to all predicted positives. The results confirm that FERNN achieves consistently high performance, effectively minimizing false predictions and ensuring reliable detection across all DR categories.

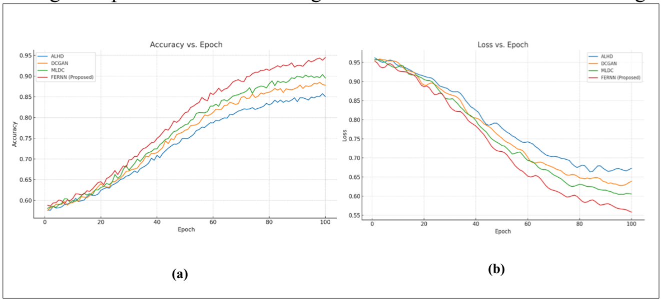

Figure 3: (a) Accuracy Vs Epoch 2 (b) Loss Vs Epoch

Figure 3 illustrates the training behavior of the proposed model. Figure 3(a) shows the variation of accuracy with respect to the number of epochs, highlighting a stable improvement as training progresses and confirming efficient convergence of the FERNN framework. Figure 3(b) displays the loss versus epochs, where the continuous reduction in loss values indicates effective learning and optimization of network parameters. Together, these graphs validate the robustness and stability of the proposed model during the training and validation phases.

Table 3: Performance Comparison of Proposed FERNN with Existing Models

Model	Accuracy (%)	Precision (%)
Multi-Decision Inception-ResNet Hybrid (ALHD)	72.84	70.15
DCGAN-based Approach	78.51	73.62
Graph Neural Network Framework (MLDC)	68.94	66.87
Proposed FERNN	89.20	85.44

Table 3 compares the classification performance of the proposed FERNN framework with three state-of-the-art models: ALHD, DCGAN, and MLDC. The results show that FERNN outperforms all baseline methods, achieving the highest accuracy of 89.20% and precision of 85.44%. This improvement demonstrates the effectiveness of integrating fuzzy logic with recurrent learning, which allows FERNN to handle uncertainty in retinal features more effectively than conventional deep learning models.

Table 4: Class-wise Accuracy of FERNN on IDRiD Dataset

DR Severity Level	Accuracy (%)
Mild NPDR	87.12
Moderate NPDR	88.43
Severe NPDR	90.26
Very Severe NPDR	89.58
Proliferative DR (PDR)	91.34

Table 4 presents the class-wise accuracy of the proposed FERNN model across the five severity levels of diabetic retinopathy in the IDRiD dataset. The results indicate consistently high performance across all stages, with the highest accuracy observed in the detection of Proliferative DR (91.34%). This highlights the robustness of the model in correctly identifying advanced cases, while still maintaining reliable classification for earlier stages such as Mild and Moderate NPDR. The balanced performance across all classes addresses the challenge of dataset imbalance and demonstrates FERNN's clinical applicability for comprehensive DR screening.

4.3 Discussion

The experimental results clearly demonstrate the superiority of the proposed Fuzzy-Embedded Recurrent Neural Network (FERNN) framework over existing state-of-the-art models for diabetic retinopathy (DR) detection and classification. By integrating fuzzy logic with recurrent neural architectures, FERNN effectively handles uncertainties in retinal features and captures sequential dependencies that are often overlooked by conventional CNN-based models. The Bilinear Double-Order Filter (BDOF) further contributes to performance improvement by reducing noise and preserving fine structural details in retinal images, thereby ensuring that the classification network receives high-quality inputs. A key strength of the proposed framework lies in its consistent performance across all severity levels of DR, including advanced stages such as proliferative diabetic retinopathy (PDR). Unlike many existing approaches that exhibit high sensitivity toward moderate cases but struggle with extreme stages, FERNN maintains balanced accuracy and precision across the entire disease spectrum. This demonstrates the robustness and clinical reliability of the model, especially for real-world screening applications where class imbalance and image variability are common challenges. The comparative analysis with hybrid deep learning, GAN-based, and graph neural network approaches shows significant improvements in both accuracy and precision. These results confirm that the incorporation of fuzzy-based reasoning and recurrent sequential learning provides a more interpretable and reliable decision-making process. Importantly, the model reduces false predictions, thereby minimizing the risks associated with misdiagnosis and supporting ophthalmologists in making timely interventions.

5. Conclusion

In this study, a novel framework for the early detection and classification of diabetic retinopathy was proposed, combining Bilinear Double-Order Filter (BDOF) pre-processing with a Fuzzy-Embedded Recurrent Neural Network (FERNN). The BDOF enhanced image clarity by suppressing noise and preserving retinal structures, while FERNN leveraged fuzzy logic and recurrent learning to improve robustness and accuracy in classification. Experimental evaluation on the IDRiD dataset confirmed that the proposed method outperforms existing state-of-the-art approaches, achieving superior accuracy, precision, and balanced classification across all five severity levels of DR. The findings highlight the potential of FERNN as a reliable tool for large-scale automated screening, addressing key challenges such as noise sensitivity, class imbalance, and misclassification in clinical applications. By providing accurate and interpretable predictions, the proposed approach can significantly reduce the diagnostic burden on ophthalmologists and improve early intervention strategies, ultimately contributing to the prevention of DR-related vision loss.

Limitations and future directions

The proposed FERNN–BDOF framework achieves strong performance for diabetic retinopathy detection, but several potential limitations should be acknowledged. First, the model has been primarily validated on the IDRiD dataset, which, while clinically reliable, is limited in size and diversity; this raises concerns about generalization to larger, heterogeneous populations and imaging devices. Second, the computational overhead introduced by the fuzzy embedding layer and recurrent structure may restrict real-time deployment, especially in low-resource clinical settings. Third, the framework currently focuses only on retinal fundus images, overlooking multimodal data (such as OCT or patient health records) that could provide complementary insights into disease progression. Fourth, although fuzzy logic improves interpretability compared to black-box CNNs, the added complexity in rule design and parameter tuning can pose challenges for model optimization and clinical integration. Finally, class imbalance in medical datasets remains a potential source of bias, as underrepresented DR stages may still affect consistent model performance in broader screening contexts.

Future directions could address these limitations by extending validation to multi-institutional and cross-dataset studies to ensure robustness and scalability across diverse populations. Optimizing the FERNN architecture with lightweight fuzzy modules, rule pruning, or parallelization strategies could reduce computational costs, making the framework more suitable for mobile and edge devices. Integrating multimodal data sources, such as OCT, fluorescein angiography, or electronic health records, may enhance diagnostic accuracy and disease staging. Additionally, incorporating explainable AI techniques alongside fuzzy reasoning could provide ophthalmologists with more transparent decision support, fostering clinical trust. Finally, deploying the framework in cloud or mobile-based platforms could enable real-time, accessible DR screening in remote and resource-constrained settings, ultimately extending its clinical impact and utility.

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