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Power Optimized Embedded Hybrid AI Architecture for Diabetic Retinopathy Screening

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Abstract: Diabetic Retinopathy (DR) is a progressive ophthalmic complication of diabetes and a leading cause of vision impairment worldwide. Early diagnosis and accurate classification of DR stages are crucial for effective intervention and management. This study proposes a novel hybrid deep learning framework that integrates Convolutional Neural Networks (CNNs) with a modified Long Short-Term Memory (LSTM) network for the classification of diabetic retinopathy from retinal fundus images. The CNN component is employed for automated extraction of spatial features, effectively capturing localized retinal lesions such as microaneurysms, hemorrhages and exudates. To further enhance feature representation and model complex dependencies within the spatial information, a modified LSTM layer is incorporated, enabling the network to learn sequential patterns and contextual relationships across extracted features. The proposed CNN–modified LSTM model is evaluated on publicly available datasets, achieving significant improvements in classification accuracy, sensitivity, specificity, and F1-score compared to conventional CNN models and traditional machine learning classifiers. Ablation studies confirm the contribution of the modified LSTM in refining feature dependencies and improving classification robustness. The experimental results demonstrate that the proposed method offers a promising and reliable approach for automated DR detection, potentially aiding in large-scale screening and reducing the burden on ophthalmologists.

Keywords: Power-optimized architecture,Embedded system, Hybrid artificial intelligence,Diabetic retinopathy screening, Retinal image classification,Deep learning.

INTRODUCTION

Diabetic Retinopathy (DR) is a progressive eye disease that primarily affects elderly individuals and can lead to severe visual impairment or complete blindness if not diagnosed and treated at an early stage [1]. The disease results from damage to the retinal blood vessels caused by prolonged high blood sugar levels, leading to fluid leakage, blood clots, and oxygen deprivation in the retinal tissue, ultimately compromising vision. Clinically, DR is categorized into two major types: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is further subdivided into three stages, mild, moderate, and severe with severe NPDR carrying a significant risk of progressing to PDR if left untreated [2]. According to a survey conducted by the World Health Organization (WHO), approximately 950,000 individuals in the European region are currently affected by DR [3]. These findings highlight the urgent need for early detection, systematic screening, and timely intervention strategies to effectively manage and reduce the global burden of Diabetic Retinopathy [4]. Recent advancements in artificial intelligence (AI), particularly in deep learning, have shown great potential for medical image analysis and disease classification [5-9].

Convolutional Neural Networks (CNNs) have been widely employed for extracting rich spatial features from retinal fundus images, capturing critical patterns such as microaneurysms, hemorrhages, and exudates. However, CNNs alone often struggle to model long-range dependencies and contextual information across feature maps. To address this limitation, Recurrent Neural Networks (RNNs) and their variants like Long Short-Term Memory (LSTM) networks can be employed to learn temporal and sequential relationships within extracted features [10]. This study proposes a hybrid model that integrates CNN for spatial feature extraction with a modified LSTM network for sequential feature learning, enhancing classification accuracy. The CNN component captures localized retinal abnormalities, while the modified LSTM models the complex interdependencies among extracted features. This combined approach aims to improve robustness and reliability in classifying the different stages of diabetic retinopathy. Extensive experiments on benchmark datasets demonstrate that our proposed method outperforms traditional CNN-only models and conventional machine learning classifiers.

Related works

Several studies have focused on enhancing the precision and effectiveness of detecting diabetes-related vision impairments, particularly Diabetic Retinopathy (DR), a serious condition affecting eyesight.

Jabbar et al. 2024[11] proposed an efficient system for DR. The proposed system utilizes fundus imaging to capture retinal images. It utilized VGGNet architecture to detect DR. Its performance was evaluated through extensive experiments, demonstrating a classification accuracy of 97.6%, significantly surpassing the results reported in existing studies. By facilitating early and accurate diagnosis, the system offers a transformative solution, particularly for remote and underserved regions. Furthermore, it optimizes patient prioritization, ensuring that individuals with early-stage DR receive timely interventions, ultimately contributing to improved patient outcomes and reduced healthcare costs.

A Transfer Learning (TL)-based approach for DR identification has been proposed, leveraging feature extraction from ResNet-18 and ShuffleNet models[12]. For classification, they employed an Error Correction Output Code (ECOC) ensemble strategy. Additionally, the system's parameters were optimized automatically using Adaptive Differential Evolution (ADE). Their method achieved notable performance: 82% accuracy in APTOS 5-class DR grading, 96% in APTOS 2-class grading, and 75% in 3-class grading on the EyePACS dataset. However, despite these promising results, limitations persist, particularly in handling diverse datasets and variations in the severity of DR.

Ref.[13] addressed the critical concern of privacy preservation in Diabetic Retinopathy (DR) detection by employing Federated Learning within a decentralized training framework. Their approach ensured that sensitive patient data remained local while models were collaboratively trained across multiple devices. They evaluated three models: standard transfer learning, Federated Averaging (FedAVG), and Federated Proximal (FedProx), achieving DR detection accuracies of 92.19%, 90.07%, and 85.81%, respectively. While demonstrating strong performance, the study highlights the potential of federated approaches to balance data privacy with high diagnostic accuracy.

The use of ensemble learning combined with Minimum Redundancy Maximum Relevance (mRMR) feature selection to enhance DR detection has been proposed [14]. Their approach involved preprocessing images and applying MobileNet through transfer learning. For early-stage DR detection, they achieved impressive accuracies: 96% on the Messidor dataset, 895% on APTOS 2019, and 97.46% on the DDR dataset. In multiclass classification across all DR stages, their model maintained strong performance with accuracies of 96.06%, 89.86%, and 82.74% on Messidor, APTOS 2019, and DDR datasets, respectively. This work demonstrates the effectiveness of feature selection and ensemble strategies in improving DR detection, though performance variability across datasets

indicates challenges in generalization.
Ref. [15] proposed an automated ensemble deep learning (DL) model for the recognition and classification of Diabetic Retinopathy (DR). Their approach combined two powerful DL architectures: ResNeXt and a modified DenseNet-101. ResNeXt, offering improvements over previous ResNet models, introduced an enhanced split-transform-merge strategy with shortcut connections across blocks, optimizing feature transformation and learning. Meanwhile, the DenseNet component leveraged dense block concatenation to maximize feature reuse and efficiency. The final prediction was determined by ensembling the outputs from both models using a Maximum a Posteriori (MAP) estimation with normalization, thus refining classification performance. This ensemble strategy effectively harnessed the strengths of both architectures, enhancing detection accuracy and robustness in DR diagnosis.

A deep learning (DL)-based approach to classify fundus images into five Diabetic Retinopathy (DR) stages was proposd, aiming for maximum accuracy with minimal execution time. They compiled a dataset of 5,819 raw images by merging three prominent DR datasets: Messidor2, APTOS, and IDRiD. To ensure high-quality input data, various preprocessing techniques were applied to enhance image clarity and remove noise and artifacts. Their model design featured a shallow Convolutional Neural Network (CNN) architecture, consisting of three convolutional blocks and max-pooling layers, trained using a categorical cross-entropy loss function. This streamlined yet effective network highlights the potential of lightweight models in achieving fast and accurate DR classification without heavy computational demands [16].

Ref.[17] proposed a hybrid system for highly accurate identification of Diabetic Retinopathy (DR), combining deep learning (DL) and machine learning (ML) techniques. Their approach involved fine-tuning a pretrained ResNet-50 on DR images while introducing a new GraphNet124 model for enhanced feature extraction. A sophisticated feature fusion and selection process was applied: features from GraphNet124 and ResNet-50 were combined using Shannon Entropy-based selection. Additionally, the feature vector was enriched with Local Binary Pattern (LBP) and deep learning-derived features. Optimization of the final feature set was performed using metaheuristic algorithms — the Sine Cosine Algorithm (SCA) and the Binary Dragonfly Algorithm (BDA). These refined features were then fed into traditional ML classifiers for DR prediction. The system's performance was evaluated using the publicly available Kaggle EyePACS dataset, demonstrating the potential of hybrid architectures in maximizing DR detection accuracy by leveraging both DL and advanced optimization techniques.
A binary hierarchical ensemble model combining four different CNNs for DR classification has been proposed [18]. Their hierarchical strategy aimed to progressively improve decision-making accuracy by organizing multiple CNNs in a structured combination. Utilizing the Kaggle APTOS dataset, the proposed method achieved a strong performance, with an accuracy of 85.3% and a Kappa score of 0.911. These results highlight the effectiveness of hierarchical CNN ensembles in enhancing classification reliability and handling the complexity of DR grading.

From the above comprehensive review of the current state-of-the-art algorithms for DR detection systems, it has been identified that the evolution of DR detection approaches, from pure transfer learning models to sophisticated ensemble and hybrid architectures that combine deep feature extraction, intelligent feature selection, privacy-preserving training, and metaheuristic optimization. While significant accuracy improvements have been achieved, ongoing challenges include handling dataset diversity, severity variations, computational efficiency, and real-world deployment considerations.

To address the critical challenge of accurate DR grading, this work proposes an innovative framework and strategy for fundus image classification. The presented algorithm CNN- Modified LSTM combines the strengths of CNNs and LSTM networks. CNNs excel at extracting spatial features from input images, capturing essential patterns and details such as edges, textures, and shapes. On the other hand, LSTMs are well-suited for modeling sequential relationships, making them ideal for tasks where the sequence or progression of data over time or space is crucial. In the context of Diabetic Retinopathy (DR) classification, the CNN-MLSTM model can effectively capture both the visual features in the fundus images and the temporal or sequential progression of DR stages, which is key to accurate classification. The ability of MLSTMs to smooth predictions and reduce overfitting. Therefore, the CNN-MLSTM model is chosen for precise DR grading.

METHODOLOGY

The Figure.1 represents a complete automated pipeline for classifying diabetic retinopathy using a hybrid AI model. First, the retinal image undergoes pre-processing, where techniques like Contrast Limited Adaptive Histogram Equalization and circular averaging filters are applied to enhance clarity. Next, blood vessels are segmented using the Coye filter to highlight vascular structures. The system then performs abnormality segmentation, separately detecting hemorrhages, microaneurysms, and hard exudates—key clinical indicators of diabetic retinopathy. After these abnormalities are identified, the relevant characteristics are gathered during the feature extraction stage. Finally, these features are fed into a modified RNN-LSTM classifier, which categorizes the eye condition into various stages such as Normal, Mild/Moderate/Severe NPDR, or PDR with or without Macular Edema (ME). This structured approach ensures accurate, stage-wise diabetic retinopathy detection.

Messidor Database

This database was used to obtain the NPDR images. This dataset was created by the Department of Ophthalmology in France to support researchers and educators. The Messidor project database includes 1200 retinal images that were captured using a 3CCD shading camera on a Top-con TRC NW6 non-mydriatic retinography 18 with a 45 degree field of view. For each shading plane, the images are captured in bits of 8 at 1440 x 960, 2240 x 1488, and 2304 x 1536 pixels.

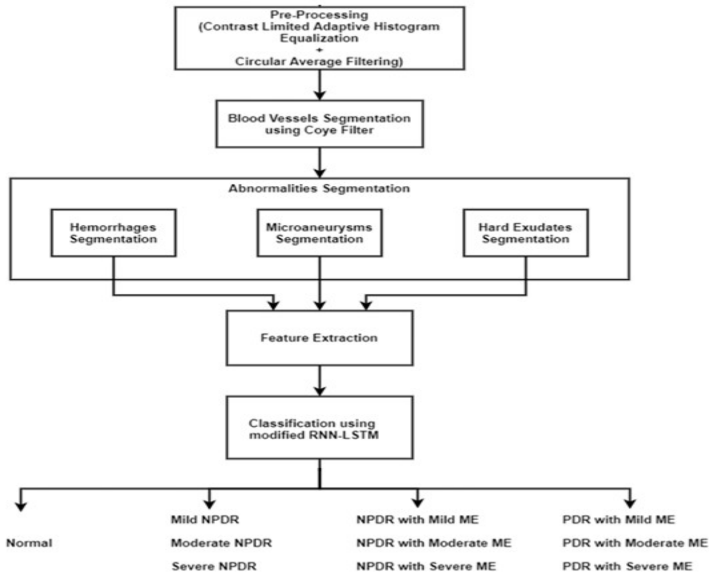


Figure 1 Proposed Methodology

Pre-processing

Since raw fundus images are prone to errors and noise, they cannot be directly used for ophthalmic image processing. Various factors such as iris color variations, differences in skin pigmentation, improper lens placement, and poor camera contrast contribute to inter and intra pixel variability in the images. These variations can significantly limit the performance of diabetic retinopathy (DR) abnormality detection. Image preprocessing plays a crucial role in suppressing these undesirable artifacts without affecting the actual image data. Figure 2 illustrates the sequence of steps carried out during the preprocessing stage.

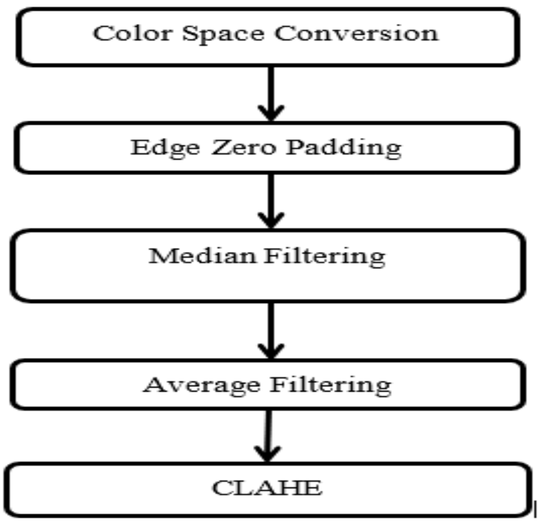


Figure 2. Block diagram of preprocessing process

The preprocessing pipeline begins with Color Space Conversion, which transforms the image into a color model better suited for feature extraction. This is followed by Edge Zero Padding to maintain the original image dimensions during filtering. Median Filtering is then applied to remove impulsive noise while preserving edges. To further smoothen the image and minimize minor variations, Average Filtering is employed. Finally, CLAHE (Contrast Limited Adaptive Histogram Equalization) enhances the local contrast of the image, making important retinal features more distinguishable without amplifying noise. Together, these steps significantly improve the quality of raw fundus images, providing a reliable foundation for subsequent DR abnormality detection processes.

After preprocessing, the fundus images are passed into a hybrid deep learning model combining CNN and LSTM architectures with ResNet-50 as the backbone.for feature extraction and classification. CNNs are highly effective in analyzing medical images as they automatically learn hierarchical patterns such as edges, textures, and complex structures associated with diabetic retinopathy abnormalities. By working on preprocessed images, the CNN can focus more accurately on meaningful retinal features, reducing the risk of misclassification caused by noise or variability. This leads to improved detection accuracy and supports the early diagnosis and treatment of DR.

CNN- Network Architecture

CNNs automatically learn hierarchical features through convolutional layers, capturing edges, textures, and complex patterns. They consist of key components such as convolutional layers for feature extraction, pooling layers for dimensionality reduction and fully connected layers for classification. In this topology, ResNet-50 is utilized for feature extraction.

Architecture of ResNet-50

The general architecture of ResNet-50 is represented in figure 3.

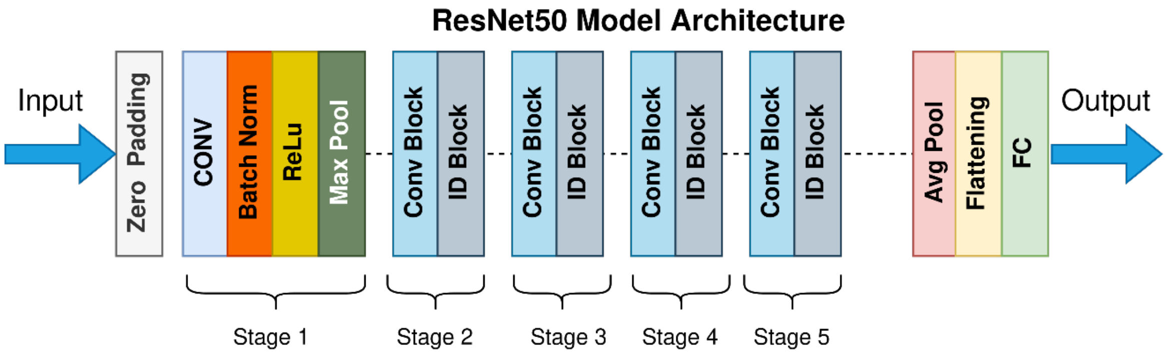


Figure 3. Architecture -ResNet-50

ResNet-50 consists of 50 layers, mainly composed of convolutional layers, batch normalization layers, ReLU activations, and fully connected layers.

- Input Layer: Accepts input images (e.g., 224×224×3 for RGB images).
- Convolutional & Max Pooling Layers: Extract initial features from the image.
- Residual Blocks: Stacked bottleneck residual blocks, each containing three layers:
    - 1×1 Convolution (Compression layer)
    - 3×3 Convolution (Feature extraction layer)
    - 1×1 Convolution (Expansion layer & dimension restoration)
- Global Average Pooling: Reduces the spatial dimensions before classification.
- Fully Connected (FC) Layer: Outputs class probabilities using a softmax activation function.

It utilises categorical cross-entropy loss. The extracted features include the count of exudates, count of hemorrhages, count of microaneurysms, textures and low-level features. Then, these features are reshaped and fed into an LSTM to learn complex dependencies between features over a sequence.

Architecture of Modified LSTM

Standard Recurrent Neural Networks (RNNs) suffer from short-term memory due to a vanishing gradient problem that emerges when working with longer data sequences. The LSTM model can improve the traditional Recurrent Neural Network (RNN), and introduces a gated unit mechanism to inhibit the gradient disappearance to a certain extent. Due to the capacity of processing time series data, the LSTM model has been applied to the field of time series prediction and has made great achievements. The LSTM neuron has the input gate, output gate, and forget gate. The input gate mainly processes input data. The forget gate determines the current neuron's retention of historical information. The output gate represents the output result of the neuron.

The Modified RNN-LSTM is used for the classification. A conventional CNN is composed in numerous layers like transmission networks. As isolated from the forwarding LSTM-RNN stream, a sub-sampling segment might include numerous co-evolutionary layers. This multi-layer system utilizes totally incorporated structures. The LSTM-RNN is demonstrated from an overall point of view for the processing and simple handling of 2D images. For quicker image processing, LSTM-RNN permits local connections of various weights. The architecture of RNN-LSTM presented in Figure 4.

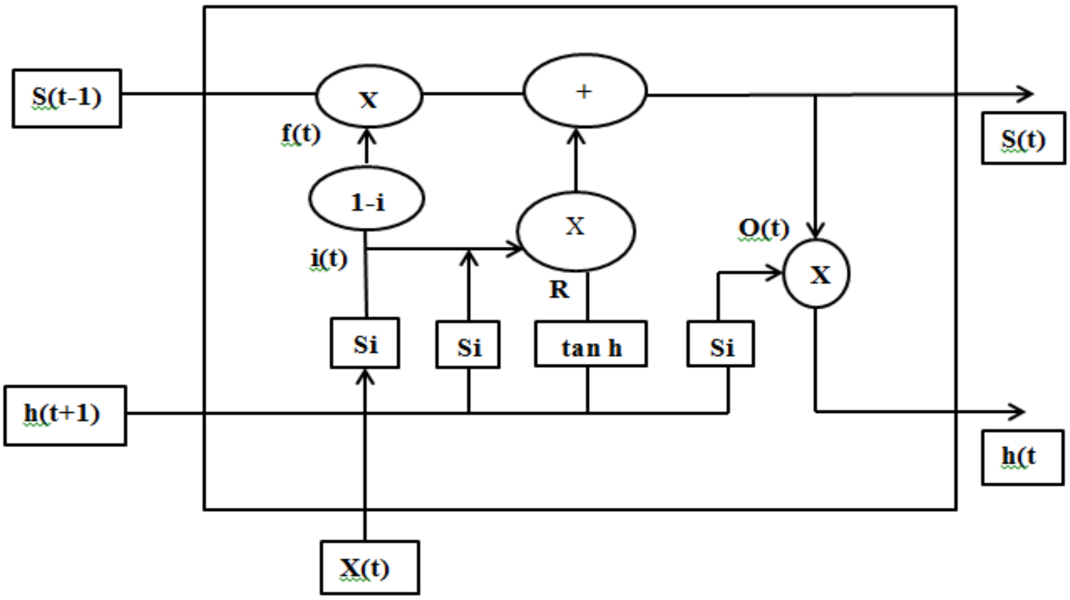


Figure 4. RNN-LSTM Architecture

Long Short-Term Memory (LSTM) networks are a modified version of recurrent neural networks, which makes it easier to remember past data in memory. The vanishing gradient issue of RNN is settled here. LSTM is appropriate to characterize, measure and anticipate time series given delays of unknown duration. It trains the model by using back-propagation. In an LSTM network, three gates are present. In this LSTM architecture the cell status store cell status. Based on current input LSTM takes decision that how much past information is to delete. This action is performed with the help of Forget gate. Once past information is deleted then new information is added to the cell using Information gate. The equations are

$$i(t) = S_i(W_{xi}X_t + W_{hi}h_{t-1} + b_i) \quad (1)$$

$$f(t) = S_i\,(W_{xf}X_t + W_{hf}h_{t-1} + b_f) \quad (2)$$

$$g = tanh(W_{xg}X_t + W_{hg}h_{t-1} + b_g) \quad (3)$$

$$O(t) = S_i(W_{xo}X_t + W_{ho}h_{t-1} + b_o) \quad (4)$$

$$s(t) = S(t-1) * f(t) + i(t) * g \quad (5)$$

$$h(t) = tanh\, tanh\, (s(t)) \, * o(t) \quad (6)$$

After removing 'tanh' from the h(t) equation the architecture become more accurate and error rate has been reduced.

New activation function called "LReLu-tanh" is used. The activation can be expressed as given below,

$$f(x) = \frac{2}{(1+e^{-2f_{lr}})} - 1 \quad (7)$$

Where,

$$f_{lr}(x) = 1(x < 0)(\alpha x) + 1(x \geq 0)(x) \quad (8)$$

After modification new equations are highlighted as,

$$i(t) = S_i(W_{xi}X_t + W_{hi}h_{t-1} + b_i) \quad (9)$$

$$f(t) = (1 - i) \quad (10)$$

$$g = tanh(W_{xg}X_t + W_{hg}h_{t-1} + b_g) \quad (11)$$

$$(t) = S_i(W_{xo}X_t + W_{ho}h_{t-1} + b_o) \quad (12)$$

$$s(t) = S(t-1) * f(t) + i(t) * g \quad (13)$$

$$h(t) = f_{lr}\,(s(t) * o(t)) \quad (14)$$

In the proposed model, LSTM is incorporated after feature extraction by ResNet-50 to enhance the classification of diabetic retinopathy stages. While ResNet-50 extracts 2048 deep features that capture spatial characteristics such as textures, lesions, and vessel abnormalities, LSTM is utilized to model the sequential relationships among these features. By treating the extracted features as a sequence, LSTM learns long-term dependencies and contextual patterns that are critical for accurately distinguishing between different stages of diabetic retinopathy. Unlike fully connected layers that map features directly to output classes, LSTM can remember and analyze the interdependencies across the feature space, leading to improved classification performance. This integration allows the model not only to detect the presence of abnormalities but also to understand the complex progression of the disease across the retina, resulting in a more robust and accurate diagnosis.

RESULTS AND DISCUSSION

The proposed methodology was implemented using MATLAB 2021a, with hardware requirements including 4 GB RAM, a 500 GB hard disk, and an Intel i3 processor. The results obtained are discussed in this section. For the pre-processed NPDR images, the PSNR and MSE values achieved were 25.9606 and 164.82, respectively. Similarly, for the pre-processed PDR images, the PSNR and MSE values were 25.0853 and 159.1602, respectively. The methodology was tested on NPDR images from the Messidor database, which consists of 12 folders, each containing 100 images, resulting in a total of 1200 images. Additionally, PDR images from the IDRiD database were analyzed. Furthermore, the performance of the proposed approach was evaluated using metrics such as F1-Score, Error Rate, Accuracy (Acc), Specificity (Sp), Precision, Sensitivity (Se), and Error Rate (E).

A. NPDR images

Table 1 Performance Results on NPDR images

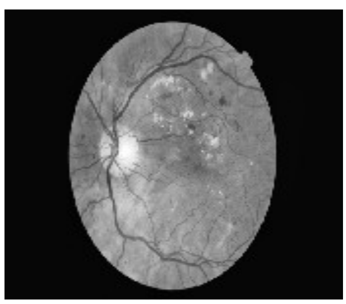
	precision	recall	f1-score	support
0	1.00	1.00	1.00	177
1	1.00	1.00	1.00	41
2	0.98	0.96	0.97	54
3	0.98	0.99	0.98	88
accuracy			0.99	360
macro avg	0.99	0.99	0.99	360
weighted avg	0.99	0.99	0.99	360

Classification of Retinopathy Grade

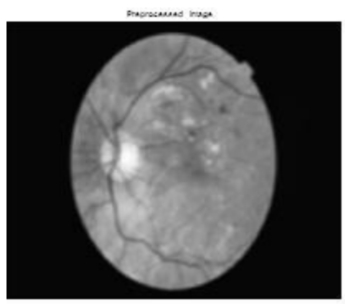
	Accuracy	Sensitivity	Specificity	Precision	F1-Score	Error Rate
Class 0	0.9972	0.9965	1.0000	1.000	0.9983	0.0028
Class 1	0.9944	1.0000	0.9941	0.913	0.9545	0.0056
Class 2	0.9972	0.9804	1.0000	1.000	0.9901	0.0028

Classification of Risk of Macular Edema

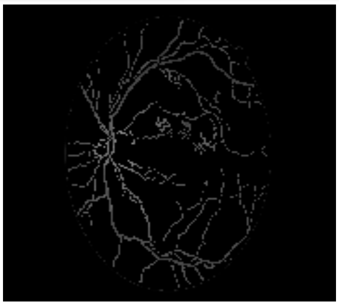
(i) Input Image



(ii) Contrast Enhanced Image



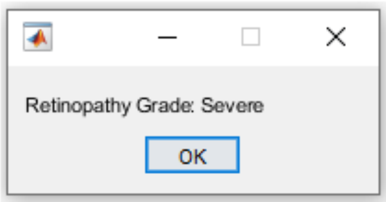
(iii) Circular Average Filtered Image



(iv) Blood Vessel

(v) Hemorrhages

Figure 5. Results on NPDR Images



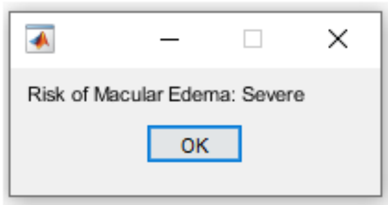


Figure 6. Dialogue window for classification of Retinopathy Grade and Macular Edema

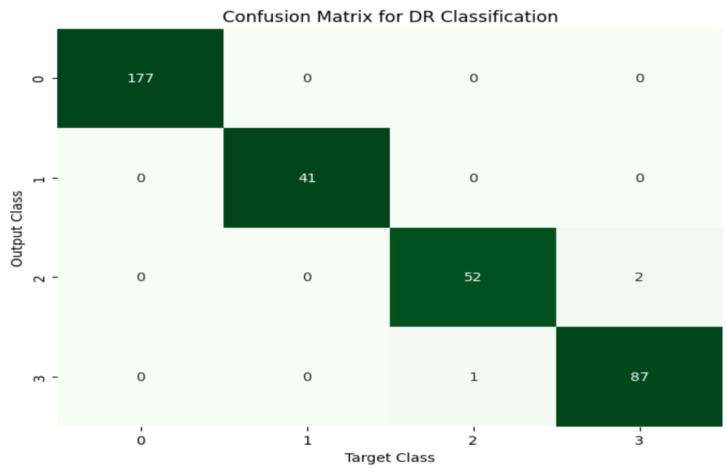


Figure 7 Confusion Matrix on Classification: 1 (Retinopathy Grade)

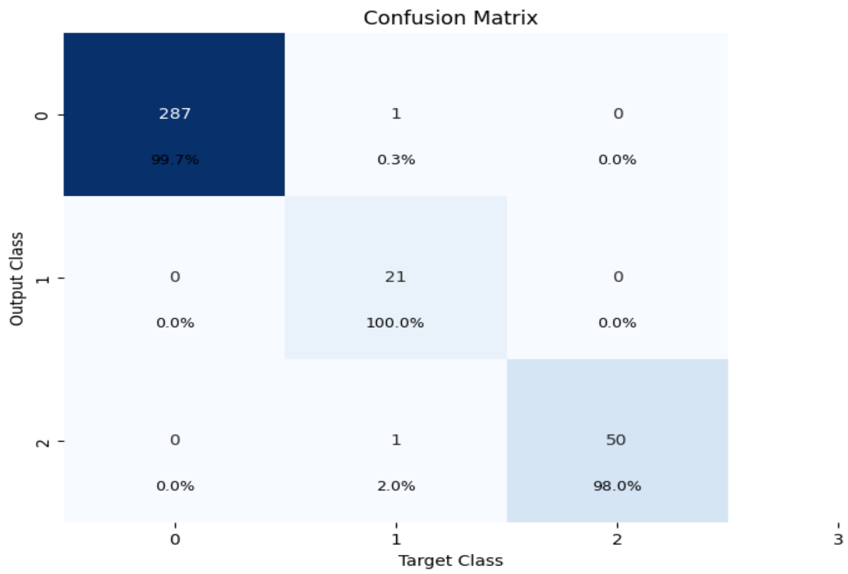


Figure 8. Confusion Matrix on Classification:2 (Macular Edema)

The classification report on Classification of Retinopathy Grade in Table 1 and Figure 7 indicates outstanding performance of the proposed model. Classes 0 and 1 achieved a perfect precision, recall, and F1-score of 1.00, showing no misclassifications. Class 2 and Class 3 also performed very well, with precision and recall values close to 0.98 and 0.96–0.99, respectively. The overall accuracy of the model is 99%, with both macro and weighted averages at 0.99, highlighting excellent consistency across all classes. These results demonstrate that the model is highly effective at distinguishing different stages of diabetic retinopathy. Minor variations in Class 2 suggest very minimal room for improvement.

The classification report on Classification of Risk of Macular Edema in Table 1 and Figure 8 indicates outstanding performance of the proposed model. The performance evaluation across three classes shows excellent results. Class 0 and Class 2 achieved a high accuracy of 99.72% with a perfect specificity and precision of 1.000, and extremely low error rates of 0.0028. Class 1 also performed well with an accuracy of 99.44% and sensitivity of 1.000, although its precision dropped slightly to 0.913, leading to a minor increase in the error rate to 0.0056. The F1-Scores across all classes remained very high, ranging from 0.9545 to 0.9983. Overall, the results confirm that the proposed model provides highly reliable and robust classification performance.

B. PDR Images

The classification of risk for Macular Edema depicted in table 2 using the IDRiD database achieved an impressive accuracy of 92.3%. The system demonstrated a very low error rate of only 7.7%, indicating strong model performance. Sensitivity and specificity both reached a perfect 100%, showing that the model is highly reliable in correctly identifying positive cases and correctly excluding negative cases. This outstanding balance between sensitivity and specificity highlights the model's robustness. Overall, the classification results reflect the effectiveness of the approach in diagnosing Macular Edema risk.

Table 2. Performance Results on NPDR images

Database	Classification of Risk of Macular Edema			
	Acc (%)	E (%)	Sen (%)	Spe (%)
IDRiD	92.3	7.7	100	100

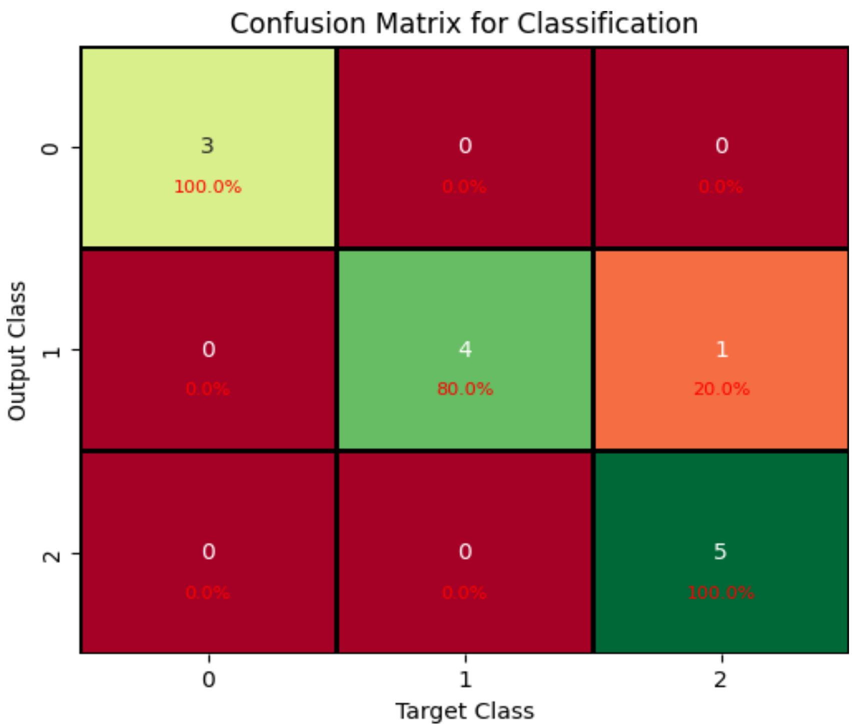


Figure 9 Confusion Matrix on Classification: 2 (Macular Edema)

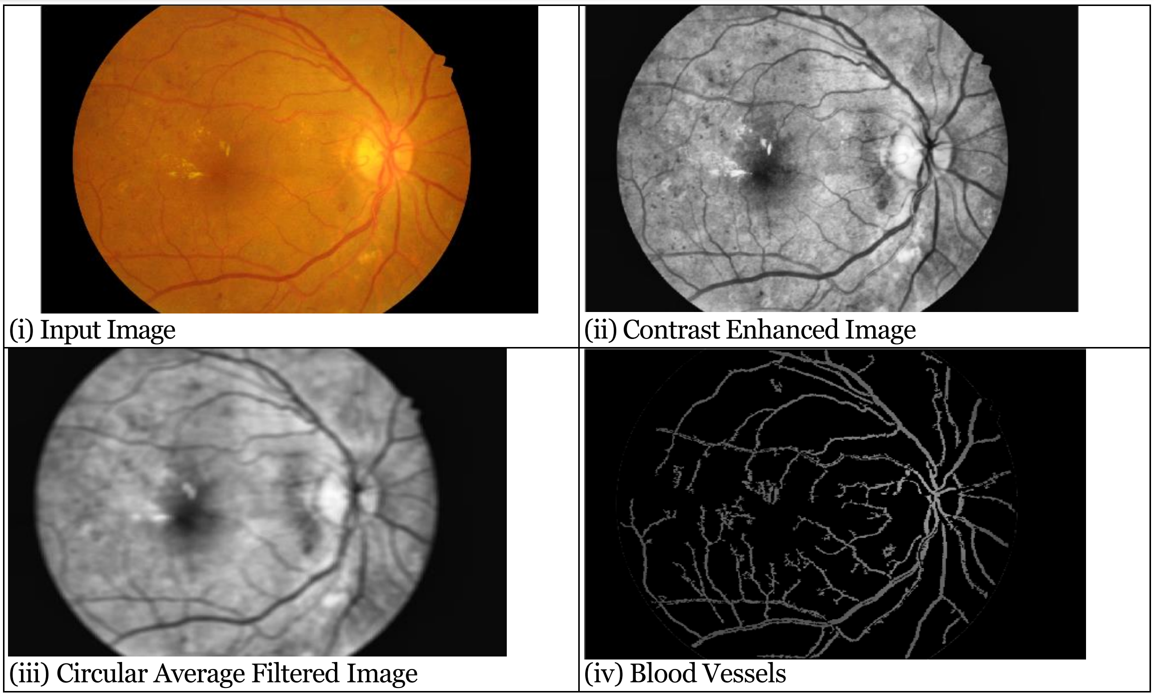


Figure 10 displays the visualization of PDR Results

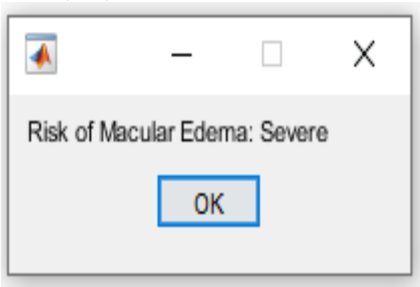


Figure 11 Dialogue window for Classification of Risk of Macular

Table 3 . Validation Results of Total (NPDR from Messidor + PDR from IDRiD)

Method	Classification of Type of Retinopathy					
	Acc (%)	E (%)	Sen (%)	Spe (%)	Pre (%)	F1(%)
CNN	89.87	10.13	94.13	85.81	95.19	94.66
RF	95.47	4.53	100	90.55	95.46	97.68
Proposed	99.73	0.27	100	94.12	99.72	99.86

Table 4 . Validation Results of NPDR from Messidor Retinopathy Grade Classification

Method	Classification of Retinopathy Grade					
	Acc (%)	E (%)	Sen (%)	Spe (%)	Pre (%)	F1 (%)
CNN	505	41.94	636	79.78	50.85	50.92
RF	633	31.66	87.57	66.12	64.61	594
Proposed	95.6	4.4	100	100	94.56	93.57

Table 5. Validation Results of NPDR from Messidor Macular Edema Classification

Method	Classification of Risk of Macular Edema					
	Acc (%)	E (%)	Sen (%)	Spe (%)	Pre (%)	F1 (%)
CNN	76.67	23.33	87.88	52.38	43.48	43.55
RF	83.61	16.38	96.63	257	57.25	46.42
Proposed	99.4	0.6	100	941	949	912

Table 6 Validation Results of PDR from IDRiD

Method	Classification of Risk of Macular Edema					
	Acc (%)	E (%)	Sen (%)	Spe (%)	Pre (%)	F1 (%)
CNN	84.2	15.8	94	95.7	85.9	89.2
RF	87.8	12.2	100	99.3	84	90.02
Proposed	92.3	7.7	100	100	93.33	93.26

The accuracy for overall classification of retinopathy images are 99.73% and for NPDR is 95.6% and 99.4% is for risk of Macular Edema and PDR is 92.3%. The performance of the detection of diabetic retinopathy using proposed method is compared with some of the existing works. The values of Precision, F1 Score, Error rate, Accuracy, Specificity and Sensitivity are compared and tabulated in Table 7.

Table 7 Comparison of Performance of Diabetic Retinopathy Classification for Proposed Method with Existing Methods

Work	Accuracy (%)	Error Rate (%)	Precision (%)	F1 Score (%)	Sensitivity (%)	Specificity (%)
Govindaraj et al. (2019)	98	2	96	98	90	98
Gangwar & Ravi (2021)	82.18	-	-	-	-	-
Baget-Bernaldiz et al. (2021)	94.79	-	-	-	97.32	94.57
Liu et al. (2021)	96.16	-	-	-	85.22	91.08
He et al. (2021)	84.08	-	-	-	-	-
Proposed	99.73	0.27	99.72	99.86	100	100

The performance comparison shows that the proposed method outperforms previous works significantly. It achieved an outstanding accuracy of 99.73% and an exceptionally low error rate of just 0.27%. Precision and F1-score values are remarkably high at 99.72% and 99.86%, respectively, with perfect sensitivity and specificity at 100%. Compared to earlier studies like Govindaraj et al. (2019) and Liu et al. (2021), the proposed model demonstrates superior diagnostic capability. This indicates a highly reliable and accurate system for detecting and classifying the target condition.

Table 8 Comparison of Performance of Classification of Risk of Macular Edema for Proposed Method with Existing Methods

Work	Accuracy (%)	Sensitivity (%)	Specificity (%)
Lim et al. (2017)	76	80	70
Marin et al. (2018)	97.4	-	-
Syed et al. (2018)	93.5	96.23	95.04
Xiaomeng Li et al. (2019)	91.2	-	-
Tanzeeha Sulaiman, J. Angel Arul Jothi (2020)	68	-	-
Rajeev Kumar Singh and Rohan Gorantla (2020)	96.12	96.32	95.84%
Proposed	99.4	100	941

The comparative analysis clearly demonstrates the superior performance of the proposed method, which achieved an accuracy of 99.4%, the highest among all evaluated approaches. Furthermore, it attained a perfect sensitivity of 100%, ensuring that all positive cases were correctly identified without omission. Although the specificity is slightly lower at 94.1%, it remains competitive relative to existing methods. Prior studies, such as those by Rajeev Kumar Singh and Rohan Gorantla (2020) and Syed et al. (2018), reported strong outcomes but did not match the comprehensive effectiveness observed in the proposed model. These results substantiate the robustness and clinical applicability of the proposed approach in achieving reliable and precise classification performance.

CONCLUSION

In this study, a deep learning-based approach integrating ResNet-50 and CNN-LSTM architectures was proposed for the detection and classification of diabetic retinopathy (DR) abnormalities. Extensive preprocessing was applied to enhance fundus images by reducing noise and improving image quality, thereby enabling more accurate feature extraction. A total of 36 significant features were extracted, covering morphological, intensity-based, GLCM texture, and wavelet features. The ResNet-50 model effectively captured high-level representations, while the LSTM network helped in modeling complex spatial relationships between features. Experimental evaluations on publicly available datasets such as Messidor and IDRiD demonstrated that the proposed methodology achieved outstanding performance, with an accuracy of 99.4% and sensitivity of 100%. Comparative analysis with existing works further confirmed the superiority of the proposed system. The results highlight that the model is highly robust, reliable, and suitable for real-world clinical applications for early detection and classification of DR, contributing to timely and efficient patient care.

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