



# Analysis and Classification of Diabetic Retinopathy Using Deep Learning

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**Abstract:** Diabetic Retinopathy (DR) is a severe microvascular complication of diabetes and one of the leading causes of preventable blindness worldwide. Early diagnosis and accurate classification of DR stages are essential for timely medical intervention and effective treatment. However, traditional manual screening of retinal fundus images by ophthalmologists is time-consuming, subjective, and prone to inter-observer variability. This paper presents an automated system for the Analysis And Classification Of Diabetic Retinopathy using Deep Learning techniques. The proposed approach utilizes retinal fundus images collected from standard public datasets such as Kaggle and clinically sourced datasets. Image preprocessing and enhancement techniques are applied to improve retinal feature visibility, followed by deep feature extraction using a Convolutional Neural Network (CNN) based on the ResNet50 architecture. The trained model classifies retinal images into distinct DR severity stages, including No Diabetic Retinopathy, Mild Diabetic Retinopathy, and Severe Diabetic Retinopathy. Experimental evaluation demonstrates that the proposed system achieves high classification accuracy, sensitivity, and specificity, making it suitable for real-world screening applications. A user-friendly graphical interface is also developed to assist clinicians by providing rapid and reliable DR predictions. The proposed system serves as an effective computer-aided diagnosis tool, reducing screening workload and improving early detection of diabetic eye diseases.

**Keywords:** Diabetic Retinopathy, Deep Learning, Convolutional Neural Networks, ResNet50, Medical Image Analysis, Retinal Fundus Images, Computer-Aided Diagnosis

## I. INTRODUCTION

Diabetic Retinopathy is a progressive eye disease caused by prolonged diabetes, leading to damage of retinal blood vessels and eventual vision loss if left untreated. With the global rise in diabetes prevalence, the demand for efficient and scalable DR screening systems has increased significantly. Early stages of DR are often asymptomatic, making regular retinal examinations crucial for prevention of blindness. Traditionally, DR diagnosis is performed by ophthalmologists through manual inspection of retinal fundus images to identify lesions such as microaneurysms, hemorrhages, and exudates. While effective, this process is labor-intensive, subjective, and impractical for large-scale population screening. Moreover, limited availability of trained specialists further restricts timely diagnosis in rural and underdeveloped regions. Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have transformed medical image analysis by enabling automatic feature extraction and accurate classification from complex visual data. Convolutional Neural Networks, in particular, have shown remarkable performance in retinal image analysis due to their ability to learn hierarchical features directly from images. This work proposes a deep learning-based framework for automated DR detection and severity classification using retinal fundus images. By leveraging the ResNet50 model and effective preprocessing techniques, the system aims to provide a reliable, scalable, and objective diagnostic solution that supports ophthalmologists and improves screening efficiency.

## II. RELATED WORK

Several studies have explored the application of deep learning techniques for automated Diabetic Retinopathy detection. Early approaches relied on traditional image processing and handcrafted feature extraction methods combined with classical machine learning classifiers. Although these methods provided reasonable performance, they were highly sensitive to variations in image quality and required extensive feature engineering. Recent research has demonstrated the superiority of CNN-based models for DR classification. Transfer learning approaches using pretrained architectures such as VGG, Inception, DenseNet, and ResNet have significantly improved

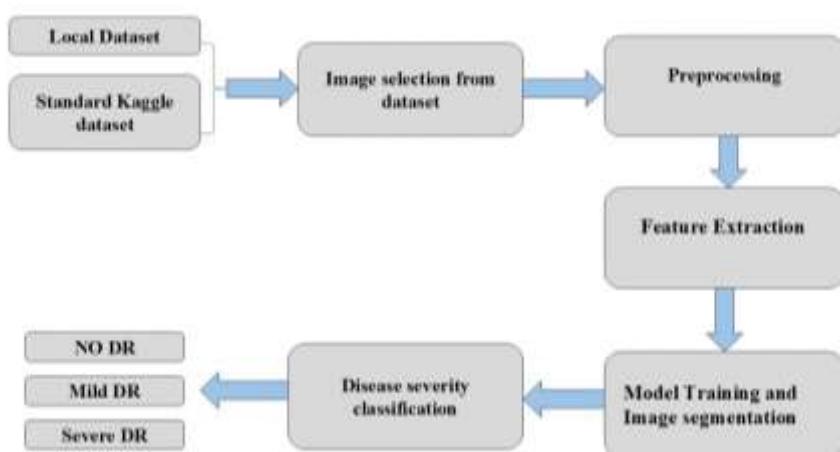


detection accuracy by leveraging large-scale image representations. Among these, ResNet-based architectures are particularly effective due to their residual connections, which enable deeper network training without degradation. Studies using large public datasets like EyePACS, APTOS, and Messidor have reported high sensitivity and specificity for multi-class DR grading. However, challenges such as class imbalance, dataset variability, and lack of interpretability still persist. Many existing systems focus either on binary classification or lack user-friendly clinical deployment interfaces.

In contrast, the proposed system integrates robust preprocessing, deep feature learning using ResNet50, multi-class DR severity classification, and a practical GUI, offering a comprehensive and clinically applicable solution.

### III. PROPOSED ALGORITHM

The proposed system follows a structured pipeline designed to automate the detection and classification of Diabetic Retinopathy from retinal fundus images.



#### 1. Local Dataset / Standard Kaggle Dataset

- This block represents the two main sources of retinal fundus images.
- Local Dataset: Images collected from hospitals or clinics, usually with real patient variations.
- Standard Kaggle Dataset: A well-known public dataset containing thousands of labelled DR images.

#### 2. Image Selection from Dataset

- From the available datasets, only usable, good-quality, correctly labelled images are selected.
- This step removes blurred, low-resolution, or incorrectly captured images.
- It ensures that the training data is clean and balanced across DR classes.
- The selected images are later divided into training, validation, and testing sets.

#### 3. Preprocessing

- Preprocessing improves the clarity of retinal images and prepares them for analysis.
- Major steps include image resizing, normalization, contrast enhancement, and noise removal.
- Techniques like CLAHE (Contrast Limited Adaptive Histogram Equalization) highlight important structures such as blood vessels and lesions.
- This step ensures that the model receives consistent, high-quality input images.

#### 4. Feature Extraction

- In this stage, meaningful visual features are extracted from preprocessed images.
- Features include microaneurysms, hemorrhages, exudates, vessel patterns, and color/texture information.
- The extracted features represent the internal characteristics of the retina that indicate disease severity.
- These features are used as inputs for training the deep learning model.

#### 5. Model Training and Image Segmentation

- Here, the deep learning model (usually a CNN) is trained on the extracted features.
- The model learns to recognize DR-related patterns by repeatedly analyzing labelled training images.
- Image segmentation may be used to isolate important retinal regions such as blood vessels or lesions, improving model accuracy.
- During training, the model continuously updates itself to minimize errors and improve prediction capability.

**6. Disease Severity Classification**

- This is the final step where the trained model predicts the severity level of diabetic retinopathy.
- Based on learned features, the system assigns each image to a category such as:
- No DR
- Mild DR
- Severe DR
- Classification helps in early diagnosis, monitoring disease progression, and supporting ophthalmologists in clinical decision-making.

**IV. PSEUDO CODE**

Input: Retinal fundus image I  
Output : Predicted Diabetic Retinopathy stage

BEGIN

// Step 1: Image Acquisition  
Read input retinal fundus image I

// Step 2: Image Validation  
IF image format is not valid THEN  
    Display error message  
    EXIT  
END IF

// Step 3: Image Preprocessing  
Resize image I to  $512 \times 512$   
Convert image to RGB format  
Normalize pixel values (0–1 range)  
Apply contrast enhancement (CLAHE)  
Remove noise using filtering

// Step 4: Model Initialization  
Load pretrained ResNet50 model  
Initialize model with trained weights

// Step 5: Feature Extraction  
Pass preprocessed image through convolution layers  
Extract deep features from feature maps

// Step 6: Classification  
Apply Global Average Pooling  
Apply Fully Connected layers  
Use Softmax activation to compute class probabilities

// Step 7: Decision Making  
Determine class with highest probability  
Assign DR stage:  
    - No Diabetic Retinopathy  
    - Mild Diabetic Retinopathy  
    - Severe Diabetic Retinopathy

// Step 8: Output Generation  
Display predicted DR stage and confidence score  
Store result in database (optional)

END

**V. RESULTS**

The performance of the proposed Diabetic Retinopathy analysis and classification system was evaluated using standard publicly available retinal fundus image datasets. The dataset was divided into training, validation, and testing sets to ensure unbiased evaluation of the deep learning model.

**Performance Evaluation Metrics**

The system was assessed using the following widely accepted metrics:

- Accuracy – measures overall correctness of classification



- Sensitivity (Recall) – evaluates the system's ability to correctly identify diseased cases
- Specificity – measures correct identification of non-diseased cases
- Confusion Matrix – provides detailed insight into class-wise predictions and misclassifications

## Experimental Results

The ResNet50-based deep learning model achieved an average accuracy of approximately 90%, demonstrating strong learning capability and reliable classification performance. High sensitivity values indicate effective detection of Diabetic Retinopathy cases, while high specificity confirms accurate identification of healthy retinal images. The confusion matrix analysis shows minimal misclassification between adjacent severity stages, validating the robustness of the model.

## Graphical User Interface Evaluation

A user-friendly Graphical User Interface (GUI) was developed to demonstrate real-world applicability. The GUI allows users to:

- Upload retinal fundus images
- View predicted DR stage instantly
- Obtain clear and interpretable classification output

The real-time prediction capability and intuitive design make the system practical for clinical screening, tele-ophthalmology, and decision-support applications, particularly in resource-limited healthcare settings.



Fig 4.1 User Interface

miniprojectb2024@gmail.com

Email address

Password

Remember me [Forgotpassword?](#)

**Sign in**

Not a member? [Register](#)

Fig 4.2 User Login

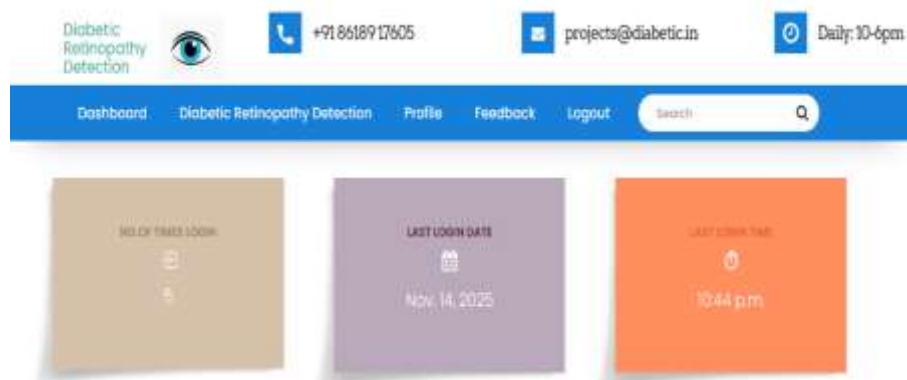


Fig 4.3 Dashboard of User

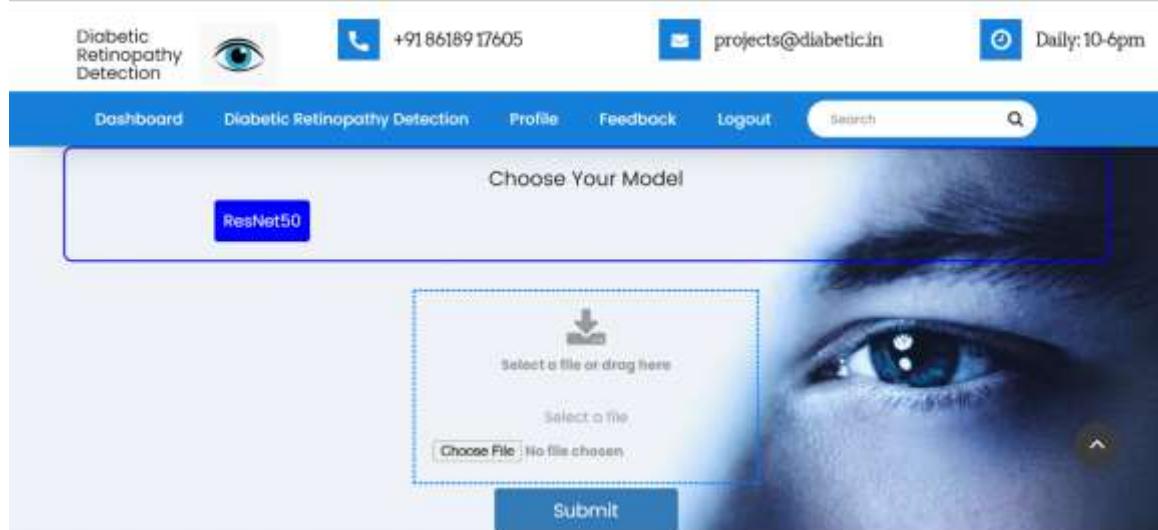


Fig 4.4 Image Input Interface

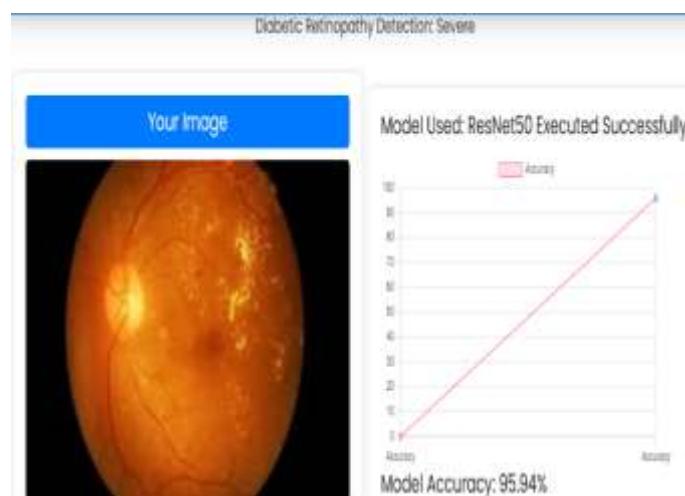


Fig 4.5 Image Predicted Output with Accuracy

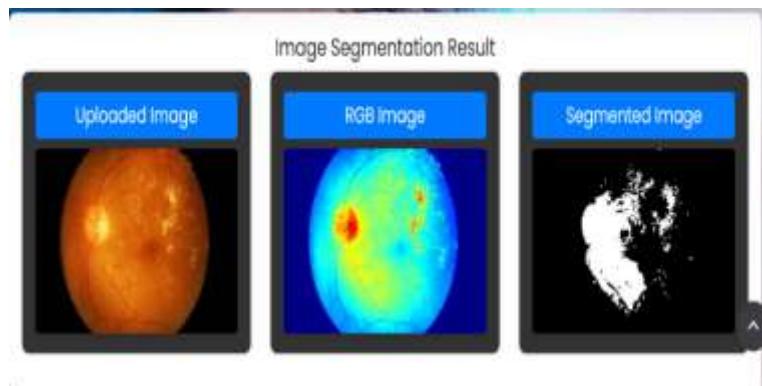


Fig 4.6 Image Segmentation Result

## VI. CONCLUSION AND FUTURE WORK

This project successfully presents an automated system for the analysis and classification of Diabetic Retinopathy using Deep Learning techniques. Diabetic Retinopathy is one of the leading causes of preventable blindness, and early detection plays a crucial role in effective treatment and vision preservation. The proposed system addresses the limitations of manual screening methods, such as subjectivity, time consumption, and dependency on expert availability. The system utilizes retinal fundus images collected from standard datasets and applies effective image preprocessing techniques including resizing, normalization, noise reduction, and contrast enhancement to improve image quality. A ResNet50-based Convolutional Neural Network is employed to automatically extract deep features and classify images into distinct severity levels: No Diabetic Retinopathy, Mild Diabetic Retinopathy, and Severe Diabetic Retinopathy.

Experimental evaluation demonstrates that the proposed model achieves an average classification accuracy of approximately 90%, along with high sensitivity and specificity. These results confirm the robustness and reliability of the system in identifying diabetic retinal abnormalities. The confusion matrix analysis further validates the model's ability to distinguish between different DR stages with minimal misclassification.

To enhance practical usability, a Graphical User Interface (GUI) was developed, enabling users to upload fundus images and receive instant classification results. This real-time prediction capability makes the system suitable for clinical screening, telemedicine, and decision-support applications, particularly in regions with limited access to ophthalmologists. Overall, the project demonstrates that deep learning-based approaches can significantly improve the efficiency, accuracy, and consistency of Diabetic Retinopathy screening.

## FUTURE WORK

1. Multi-Class DR Grading
2. Explainable AI Integration
3. Larger and Diverse Datasets
4. Real-Time Clinical Deployment
5. Cloud and Mobile-Based Applications
6. Performance Optimization
7. Clinical Validation and Approval

## REFERENCES

- [1]. Ashima Gambhir. ADVANCED PRACTICES ON DETECTION AND CLASSIFICATION OF DIABETIC RETINOPATHY FROM FUNDUS IMAGE. 2020 volume-8. <https://api.semanticscholar.org/CorpusID:219616866>
- [2]. Bhaskaranand M, Ramachandra C, Bhat S, Cuadros J, Nittala MG, Sadda SR, Solanki K. The Value of Automated Diabetic Retinopathy Screening with the EyeArt System. doi: 10.1089/dia.2019.0164. Epub 2019 Aug 7. <https://pubmed.ncbi.nlm.nih.gov/31335200/>
- [3]. Flaxel CHAR, Bailey ST, Fawzi A, Lim JI, Vemulakonda GA. Diabetic retinopathy preferred practice pattern. Ophthalmology. 2020;127(1):66-P145. doi:10.1016/j.ophtha.2019.09.025



- [4]. Raja Sarobin M., V.; Panjanathan, R.; S., G.J.; L., J.A. Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks. *Symmetry* 2022, 14, 1932. <https://doi.org/10.3390/sym14091932>
- [5]. <https://www.aurolab.com/>
- [6]. G.U.Parthasharath, K.Vasantha kumar, R.Premnivas. Diabetic Retinopathy Detection Using Machine Learning. May 2022 4(1). <https://www.researchgate.net/publication/360649393>
- [7]. M. Z. Atwany, A. H. Sahyoun and M. Yaqub, "Deep Learning Techniques for Diabetic Retinopathy Classification: A Survey," in IEEE Access, vol. 10. <https://ieeexplore.ieee.org/document/9729867>
- [8]. S. M. Baba and I. Bala, "Detection of Diabetic Retinopathy with Retinal Images using CNN," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2022. <https://ieeexplore.ieee.org/abstract/document/9788368>
- [9]. Gothane, S., Raju, K.S., Bhaskar, N., Divya, G. (2022). Diabetic Retinopathy Detection Using Deep Learning. [https://doi.org/10.1007/978-981-19-1559-8\\_39](https://doi.org/10.1007/978-981-19-1559-8_39)