ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may406

Diabetic Retinopathy Detection using Machine Learning

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Publication Date: 2025/05/20

Abstract: This paper suggests an automated technique for detecting diabetic retinopathy (DR), a major cause of visual loss. Deep learning algorithms and powerful image processing techniques are used to improve the accuracy of DR categorisation. The technique employs convolutional neural networks trained on labelled fundus images, which leads to considerable gains in classification metrics over existing methods. In terms of accuracy, precision, recall, F1-score, and AUC-ROC measures, the system performs better than current approaches. Clinical validation is aided by explainable AI features that offer visual insights into predictions. This method may lessen vision loss brought on by diabetes by providing a scalable option for early DR identification.

Keywords**:** *Diabetic Retinopathy (DR), Vision Impairment, Early Detection, Automated Detection System, Fundus Images, Classification Accuracy, AI-Driven Approaches, Clinical Applications.*

How to Cite: Suyash Shinde; Vikram Yadav; Pranav Pawar; Soham Kolte; Om Shingare; Sachin Jagadale (2025). Diabetic Retinopathy Detection using Machine Learning. *International Journal of Innovative Science and Research Technology*, 10(5), 741-746. https://doi.org/10.38124/ijisrt/25may406

I. INTRODUCTION

Diabetic retinopathy (DR) is a prominent cause of blindness worldwide, particularly among diabetics. High blood sugar levels damage the blood vessels in the retina, causing visual impairment. Early identification and treatment are crucial in preventing vision loss, but manually screening retinal images is time-consuming and prone to human error.[1]

To overcome this issue, automated methods capable of detecting and classifying diabetic retinopathy phases are required. Deep learning techniques, notably Convolutional Neural Networks (CNNs), have shown considerable promise in medical picture processing, providing automated and highly accurate solutions. YOLOv8, an improved version of the YOLO (You Only Look Once) object identification model, has emerged as a powerful tool for real-time image processing and detection.[2]

This project aims to harness the power of YOLOv8 to develop a robust system for detecting and classifying diabetic retinopathy in retinal images. YOLOv8's ability to perform both fast and accurate object detection allows it to identify key features of DR such as Micro aneurysms, hemorrhages, and exudates. By leveraging YOLOv8, the system can automatically categorize DR images into stages ranging from no DR to severe DR, facilitating early intervention and improved patient outcomes. This work presents an innovative application of state-of-the-art deep learning methods to a critical healthcare problem, offering the potential for widespread use in both clinical and remote settings.[3]

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II. LITERATURE SURVEY

[Farrikh Alzami, 2019] proposed a technique for classifying diabetic retinopathy grades using fractal analysis and random forest on the MESSIDOR dataset. Their technique segmented the pictures and then calculated the fractal dimensions as features. They failed to discriminate between moderate and severe diabetic retinopathy. [Qomariah 2019] proposed an automated approach for classifying diabetic retinopathy and normal retinal pictures using a concurrent neural network (CNN) and a support vector machine (SVM)—features included exudates, haemorrhage, and microaneurysms. The author divided the suggested system into two parts: the first used neural networks for feature extraction, while the second used SVM for classification. [Kumar, 2018] proposed a technique for better diabetic retinopathy

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identification that extracts the area and number of microaneurysms from colour fundus pictures in the DIARETDB1 dataset. Fundus picture pre-processing included green channel extraction, histogram equalisation, and a morphological technique. Microaneurysms were detected using principal component analysis (PCA), contrast limited adaptive histogram equalisation (CLAHE), the morphological process, and averaging filtering, with linear support vector machine (SVM) classification. [Mohamed Chetoui, 2018] proposed a technique for detecting diabetic retinopathy utilising several textural cues and a machine learning classification model. Two characteristics, haemorrhage and exudates, are recovered using the local ternary pattern (LTP) and local energy-based shape histogram (LESH). SVM is used to train and classify extracted histograms from LTP and LESH feature vectors. [S Choudhury, 2016] proposed a technique utilising SVM to classify diabetic retinopathy and extract fuzzy C means-based features. Mathematical morphology and a top hat filter are used to remove blood vessels. Exudates and retinal vascular density were chosen as the characteristics. Fuzzy C means segmentation is used to extract exudate. Training data are mapped into SVM kernel space using the Gaussian Radial Basis function. A method for determining the various stages of diabetic retinopathy based on blood vessels, haemorrhage, and exudates was presented by [Sangwan, 2015]. The neural network obtains the features after they have been extracted by picture pre-processing.

We are now able to comprehend natural language and communicate with users in a more tailored manner thanks to powered chatbots and machine learning approaches. Their primary functions include retail, travel, media, and agricultural. They have utilised this capability to help farmers get the answers to their unanswered problems, as well as to offer them guidance and recommendations. Furthermore,

The three types of diabetic retinopathy are proliferative, mild, and moderate non-proliferative are identified from the data using SVM-based training. However, if the exudate areas in the fundus pictures are larger than an optical disc, the technique may not produce the desired results. A method for morphology-based exudate detection from colour fundus images was presented by [Morium Akter, 2014]. The model makes use of watershed transformation, logical AND operation, thresholding, erosion, dilation, greyscale conversion, and histogram equalisation. The output of the system includes a range of exudates that are impacted by diabetic retinopathy. [Handayani, 2013] proposed a soft margin SVM-based method for classifying non-proliferative diabetic retinopathy. The degree of non-proliferative diabetic retinopathy is characterised using hard exudates in retinal fundus pictures. The segmentation of hard exudates is done using mathematical morphology. However, haemorrhage and micoaneurysms are not aspects of the system. A GMM classifier-based automated approach for the diagnosis of red lesion diabetic retinopathy based on microaneurysms was proposed by Saravanan (2013). Mathematical morphology, filter-based techniques, and supervised learning techniques are used to extract the feature. Four stages are identified based on the severity level of potential microaneurysms. [Venkatalakshmi, 2011] explained an automated approach for detecting hard exudates that uses colour highlights and sharp edges as two criteria. Sharp edge detection, color-based categorisation, and optic disc extraction were the techniques used in the detection procedure. The DRIVE and DIARETDB0 datasets were used for training and testing. The system's graphical user interface (GUI) was MATLAB 7.8.

In agriculture, artificial intelligence can assist farmers in automating their operations and in using precise harvesting techniques to increase yields and quality while using less resources. In the future, the development of autonomous vehicles and unmanned aircraft will lead to scientific advancements, more practical uses in this area, and assistance in resolving the global food supply issues caused by population expansion.

III. DATASET AND TECHNIQUES

A dataset This work made use of the Diabetic Retinopathy Detection Kaggle Dataset, which is openly accessible. Pictures from publicly accessible retinopathy detection datasets were used to generate the database. There are 1000 photos with diabetic retinopathy and 1000 images without the condition in the Kaggle dataset. We selected 122 photos with diabetic retinopathy and 122 normal images from the entire number of photographs. The selected aberrant images include microaneurysms, haemorrhages, and exudates. According to Fig. 1, the presence of diabetic retinopathy is determined by the appearance, quantity, size, and distribution of exudates, microaneurysms, and haemorrhages.Exudates are bright, yellowish patches that differ slightly in hue from the optic disc. Exudates are produced by the ruptured blood vessel's lipid content. Haemorrhages are the result of blood vessel microaneurysms rupturing. Images showing severe diabetic retinopathy, the final stage of the disease, show haemorrhages and exudates spreading.

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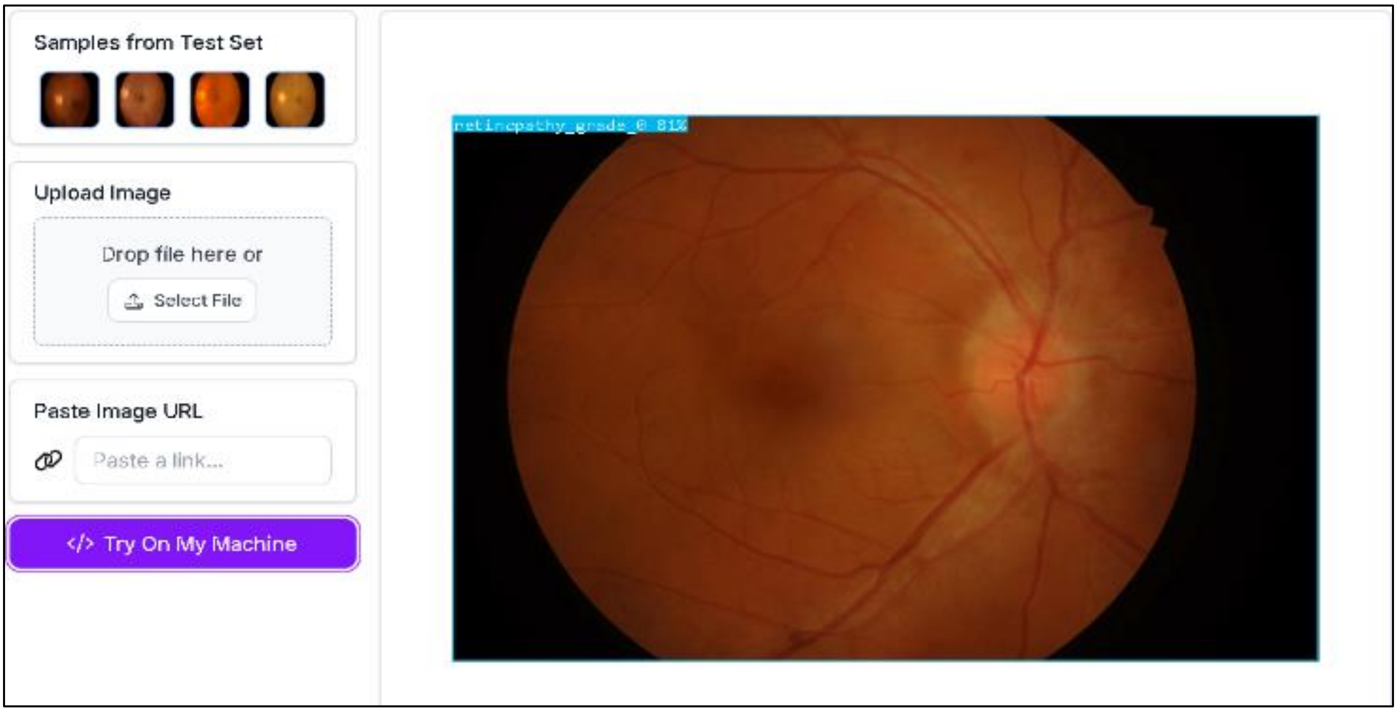

Fig 1 Using a Machine Learning Model, the Retinal Fundus Image is used to Grade Diabetic Retinopathy.

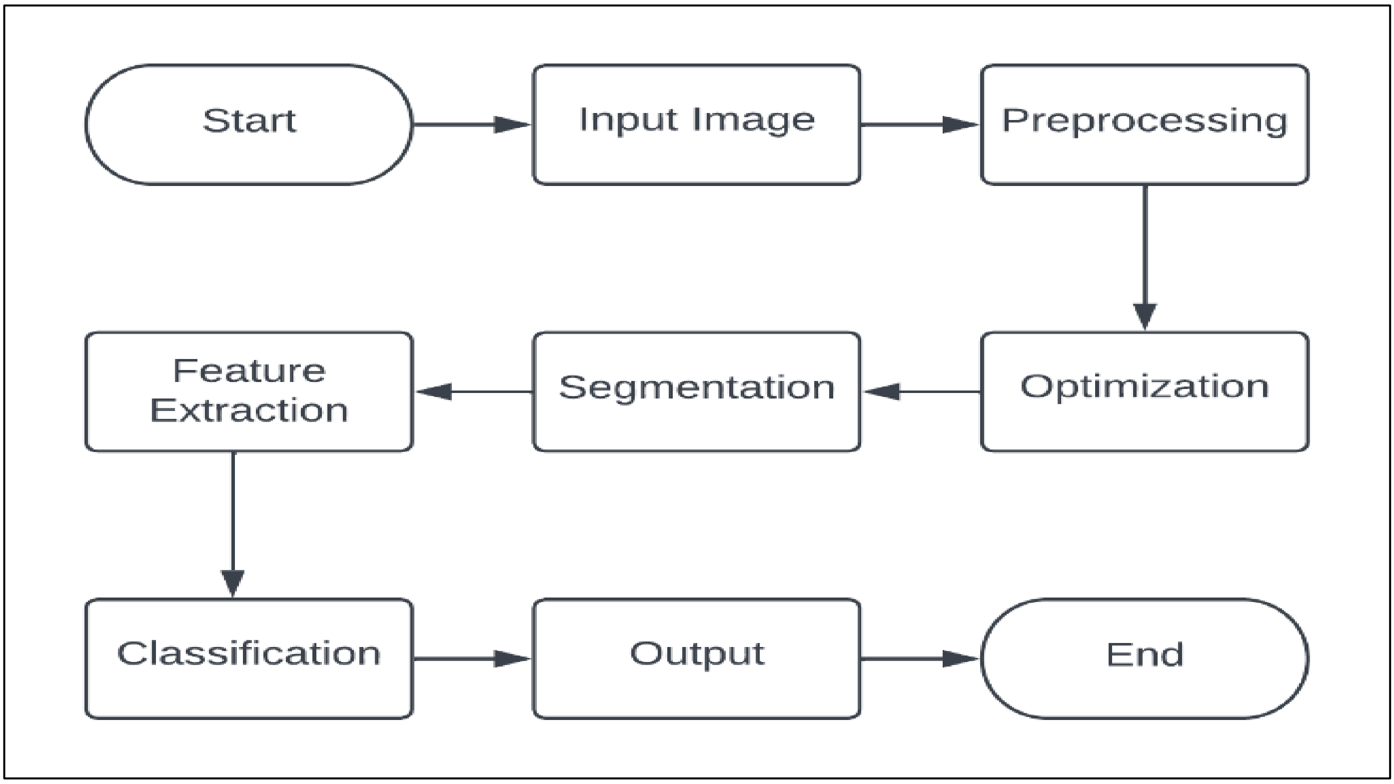

Fig 2 Process and Architecture of Diabetic Retinopathy Detection using ML

a. Prior to processing The first step in image pre-processing is to transform the dataset image to an HSV image in order to identify exudates. In order to make the translated image appear as close to the original as possible, colour space conversion is the process of transforming an image that is represented in one colour space to another. The provided image's red, blue, and green channels correspond to hue, saturation, and value. Extracting yellow-colored exudates from RGB images is helpful when converting RGB to HSV. Next, adaptive histogram equalisation, median filtering, and edge zero padding are carried out. Figure 2 displays the image prior to preprocessing. Figure 3 displays the image following pre-processing..

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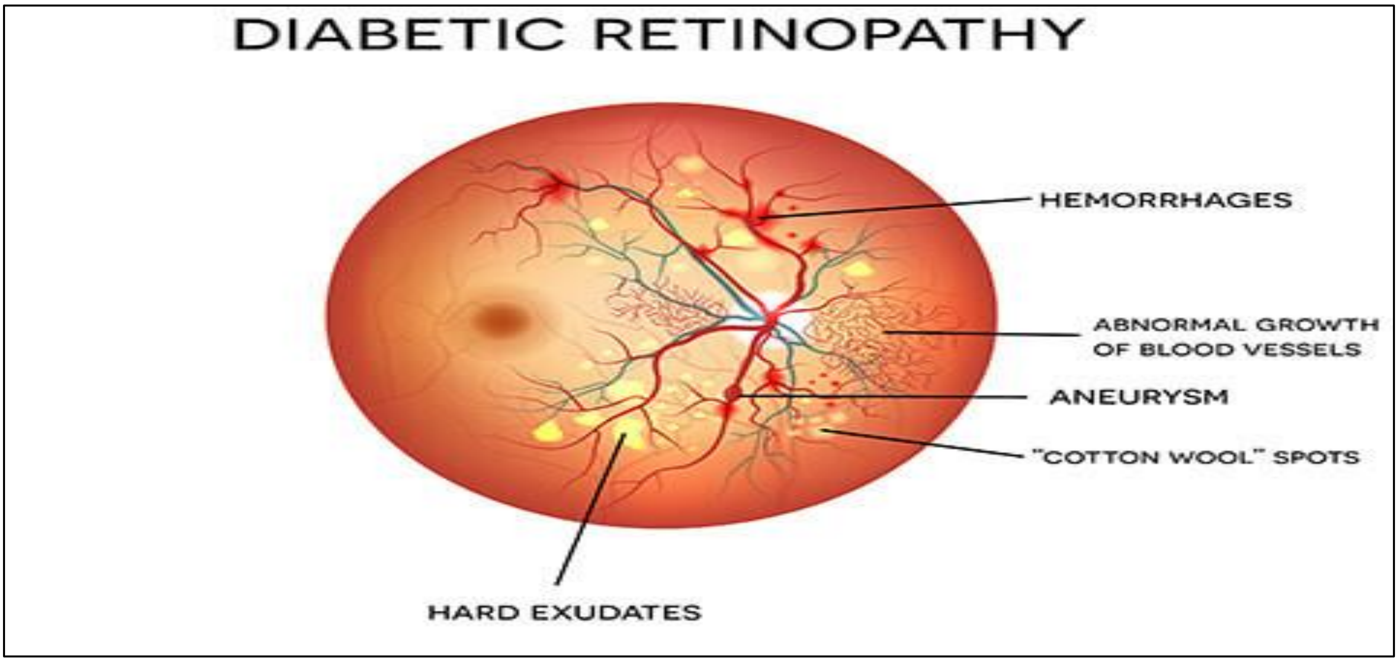
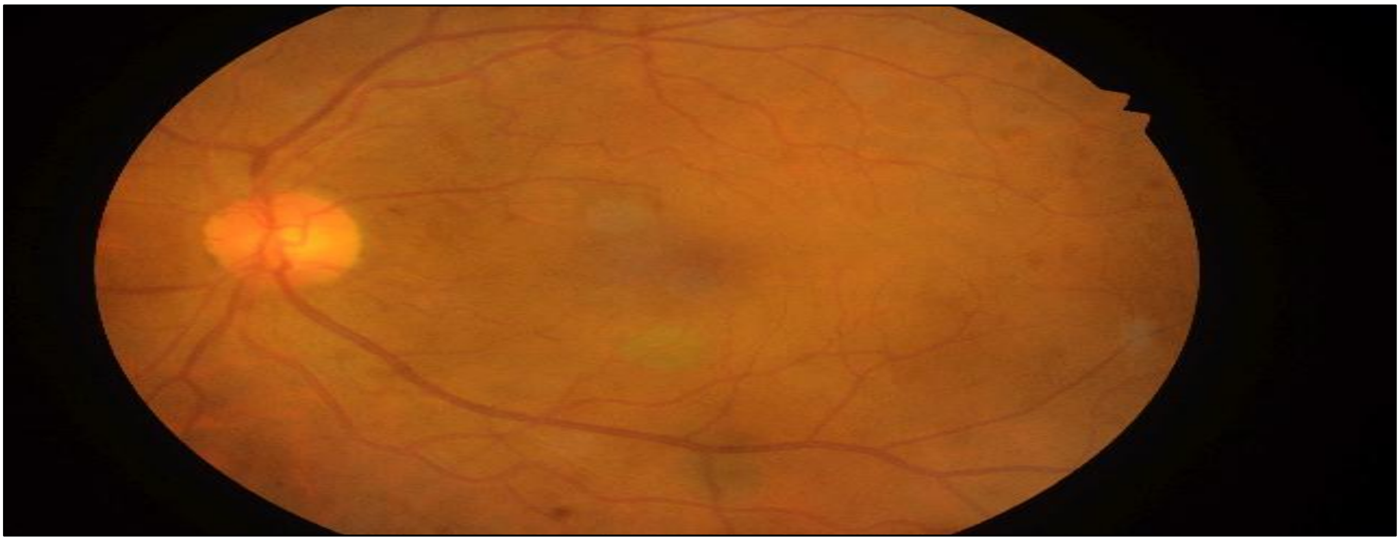


Fig 3 An Illustration of Diabetic Retinopathy



Grade 1 Indicates Microaneurysms and Mild Non-Proliferative Diabetic Retinopathy Without any Vision-Threatening Lesions.

Grade 2 Image Abnormalities with Microaneurysms and Haemorrhages

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Grade 3 Images that are Abnormal and Show Microaneurysms and Segmentation Haemorrhages

IV. CONCLUSION

In summary, the identification of diabetic retinopathy is an important field of study that makes use of developments in machine learning and image processing to offer early diagnosis and enhance treatment results. The literature study emphasises how methods have advanced from manual, traditional methods to automated, AI-powered solutions that provide greater accessibility, scalability, and accuracy. Key detection difficulties, including accessibility and efficiency in underprivileged areas, are addressed by innovations including mobile-based solutions, hybrid techniques, and deep learning models. To optimise the influence on international healthcare systems, future research should concentrate on improving model interpretability, real-time processing, and integration into clinical processes.

➢ *Future Work:*

- *Model Optimization:*

✓ *Further optimize YOLOv8 for higher accuracy and lower inference time.*
✓ *Experiment with smaller models for edge devices (e.g., mobile phones).*

- *Multi-Modal Analysis:*

✓ *Incorporate other data sources (e.g., OCT scans, clinical data) for enhanced DR detection.*

- *Advanced Classification:*

✓ *Explore multi-class classification (e.g., early vs. late-stage DR) and segmentation tasks.*

- *Clinical Integration*

✓ *Integrate the model into real-world healthcare systems for large-scale screening.*

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ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may406

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