# Early Detection of Diabetic Retinopathy Using Machine Learning

**Vishal V. Bandgar, Shardul Bewoor, Gopika A. Fattepurkar, and Prasad B. Chaudhary**

**Abstract** Early detection of Diabetic Retinopathy shields patients from losing their vision because Diabetic Retinopathy may be a typical eye disorder in diabetic patients. The elemental explanation for a visual deficiency within the populace. Thus, this paper proposes an automated method for image-based classification of diabetic retinopathy. The technique is separated into three phases: image processing, feature extraction, and image classification. The target is to naturally group the evaluation of non-proliferative diabetic retinopathy at any retinal image. For that, an underlying image preparing stage separates blood vessels, microaneurysms, and hard exudates, so on extricate highlights utilized by a calculation to make sense of the retinopathy grade.

**Keywords** Machine learning · Image processing · Diabetic retinopathy

## 1 Introduction

Diabetic Retinopathy (DR) may be a standout among the foremost successive reasons for visual debilitation in created nations. The primary source of the latest instances of visual deficiency within the working-age populace. By and huge, almost 75 individuals go dazzled every day as an outcome of DR. A viable treatment for DR requires early finding and consistent checking of diabetic patients, however, this can be a testing undertaking because the malady indicates few manifestations until it's past the purpose where it's possible to allow treatment.

As shown in above Fig. 1, Diabetic retinopathy is an eye issue that can cause Visual deficiency—little veins within the back of the attention called retinal veins

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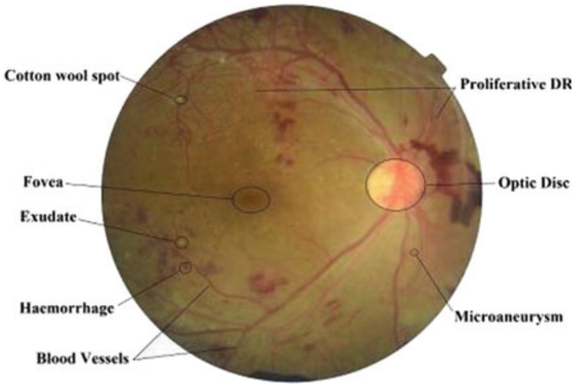


**Fig. 1** A typical colour fundus image with main fundus structures and early lesions marked

[1]. Indications of Diabetic Retinopathy are gliding spot in vision, obscured vision and blocked vision. At the purpose when the sugar level in the blood builds, blood vessels within the back of the attention finally end up frail, and seeable of this vessel releases the blood and lipoproteins liquid, at the moment liquid winds up skimming spot in vision with the goal that Diabetic patient cannot see anything totally through the vision, within the event that we do not do the treatment of this ailment on the time then it'd be conceivable of complete vision misfortune or visual deficiency [2]. On the off chance that we distinguished early the indication of Diabetic Retinopathy, it's conceivable to stay extra loss of vision.

## 1.1 Why is Machine Learning for DR?

As a value effective thanks to handling the healthcare resources, systematic screening for DR has been identified. A vital screening tool for early DR detection is that the emergence of automatic retinal image analysis. This could save both cost and time because it reduces the manual workload of grading still as diagnostic cost and time. Take, for example, the Netherlands is stated to own approximately 500,000 persons affected with diabetes, and this number is expected to extend to over 700,000 by 2030. The patients will need to undergo retinal examinations [3]. This will consequently result in a huge amount of images that would need to be reviewed. As a result, ophthalmologists will have an infinite burden and also cause an increase within the roster comprising quality of healthcare. Automated, highly accurate screening methods have the potential to help doctors in evaluating more patients and quickly routing those that need help to a specialist Machine learning may be a family of computational methods that enables an algorithm to program itself by learning from an oversized set of examples that demonstrate the specified behaviour, removing the requirements to specify rules explicitly [4]. Using established dataset and using multiple classifying algorithms to detect whether diabetic retinopathy is present or not, would bring relief to both patients further because of the resources of the healthcare system. The accuracy, sensitivity and specificity of the algorithm for detecting diabetic retinopathy (DR) can help ophthalmologists, and physicians raise the red flag and thus provide early treatment to patients and convey in exceedingly more preventive care which might bring down the burden on a healthcare Machine learning can thus help the old adage-prevention better than cure, by predicting who is more vulnerable to be in danger of DR or not [5].

**Four stages of Diabetic Retinopathy are as follows**

The first stage is known as Mild Non-Proliferative Diabetic Retinopathy (Mild NPDR). In this stage, there will expand like swelling in the veins in the retina and little inflatable like swelling in the veins known as Microaneurysms. The second stage is known as Moderate Nonproliferative Diabetic Retinopathy (Moderate NPDR). In this stage, a portion of the veins in the retina will end up blocked. The third stage is known as Severe Non-Proliferative Diabetic. This method detects and classifies the diabetic retinopathy. Preliminary results show that k-nearest neighbours obtained the best result with 68.7% for the dataset with different resolutions.

**Advantages**

Perform automated classification of Diabetic Retinopathy and component analysis in less time.

**Disadvantages**

The paper does not include testing the methods with larger data sets and classifying the subtypes of the retinopathy.

## 2 History and Background

1. Akara Sophark, Bunyarit Uyyanonvara and Sarah

Retinopathy Diagnosis using Image Mining:

The author has mainly specialized in the detection of Glaucoma and Diabetic Retinopathy. Glaucoma may be detected by the cup to disc ratio (CDR). Diabetic retinopathy may be detected by Exudates, Hemorrhages, Microneurysms and plant fibre Spots. RGB images are converted into YCbCr. Y plane is employed for detection of blood vessels, point and exudates. After candy edge detection, the image will be converted into binary to perform Skeletonization operation. DCT is employed for feature extraction. The author has proposed DCT (Discrete Cosine Transform) for feature extraction. Employed for detection of blood vessels, point and exudates. After candy edge detection, the image will be converted into binary to perform Skeletonization operation. DCT is employed for feature extraction. The author has proposed DCT (Discrete Cosine Transform) for feature extraction.

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Baraman, "Automatic Exudate Detection from Non-dilated Extracted feature goes to SVM classifier. After that Extracted feature goes to SVM classifier, after that Diabetic Retinopathy-Retinal Images using Fuzzy C-means Clustering" [7].

## 3 System Architecture

There are two categories of diabetic retinopathy: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy, where the NPDR can be subdivided into mild, moderate and severe [8]. In fact, NPDR is the most commonly diabetic retinopathy, representing 80% of all cases. The retinopathy grade diagnoses are normally provided by medical experts based on 0. Normal ($\mu A = 0$) and ($H = 0$).

1. Mild NPDR ($0 < \mu A \leq 5$) and ($H = 0$)
2. Moderate NPDR ($5 < \mu A < 15$ or $0 < H < 5$) and ($NV = 0$)
3. Severe NPDR ($\mu \geq 15$) or ($H \geq 5$) or ($NV = 1$).

where $\mu A$ is the number of microaneurysms, H the quantity of haemorrhages and NV the presence of neovascularization.

The above Fig. 2 shows the overall structure of the proposed system. It includes all the modules which we are going to implement in this project. The architecture gives an idea of input to the system, processing on that input and what will be the output of the project.

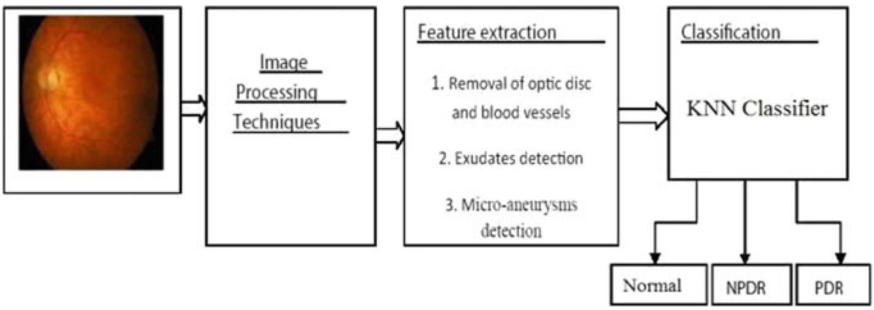


**Fig.2** Purposed systems for detection and classification of different stages of diabetic retinopathy

### 3.1 Image Database

The Messidor database [9] includes 1200 eye fundus shading numerical photos of the back shaft obtained by 3 ophthalmologic workplaces using a shading video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45° field of view. The pictures were caught implementing 8 bits for each shading plane at 1440 × 960, 2240 × 1488 or 2304 × 1536 pixels.

800 images were acquired with pupil dilation (one drop of Tropicamide at 0.5%) and 400 without dilation. The 1200 pictures are bundled in 3 sets, one for every ophthalmologic division, utilizing the TIFF position. What's more, an Exceed expectations document with therapeutic judgments for each picture is given.

In this work, we utilize the pictures of only one ophthalmologic division containing 152 pictures without retinopathy (grade 0), 30 with mellow NPDR (grade 1), 69 with moderate NPDR (grade 2), and 149 with serious NPDR (grade 3).

### 3.2 Flow Chart

The above Fig. 3 shows the flow of the project. It is divided into two parts Training Phase and Testing Phase. It shows the steps performed during the implementation. The image is preprocessed first, then from that feature extraction is done, and on the basis of that, the image is classified. The same steps are performed for the test image.

### 3.3 Activity Diagram

The above Fig. 4 shows the steps and methods of the project. The activities performed during implementation are Preprocessing, feature extraction and classification [10].

## 4 Results and Analysis

### 4.1 Extracted Features Blood Vessels

See Fig. 5.

### 4.2 Microaneurysms

See Fig. 6.

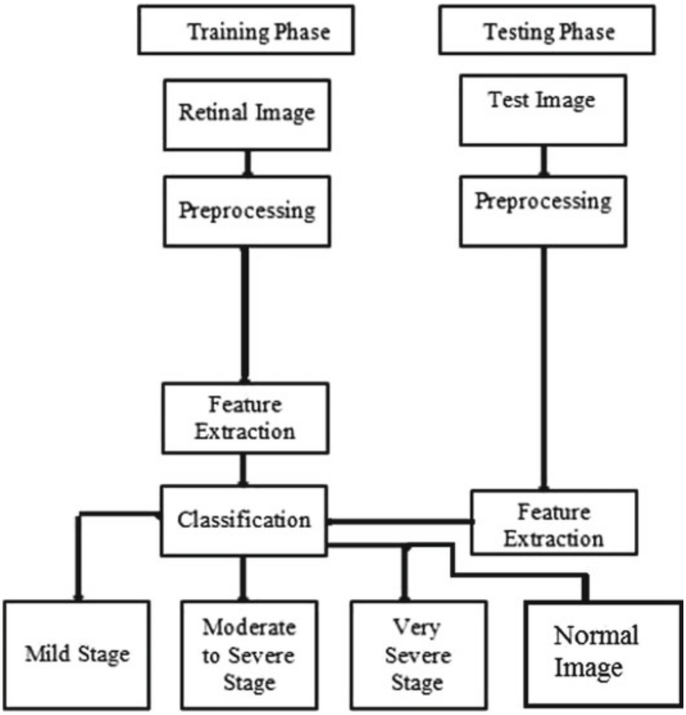


**Fig. 3** Flow chart

### *4.3 Hard Exudates*

See Fig. 7.

## 5 Conclusion

An efficient method for the detection of microaneurysms, hard exudate sand blood veins has been presented. The classifier gives an average accuracy of 88%. We conclude that image processing plays an important role in the diagnosis of DR. Future works are to detect soft exudate to improve the accuracy of retinopathy detector.

The sensitivity and specificity of binary classification are 0.8930 and 0.9089, respectively, which could be a satisfactory result. Furthermore, we developed an automatic inspection app that may be utilized in both personal examination and remote treatment. With more image data collected, we expect the accuracy is often even more enhanced, further improving our system.

Fig. 4 Activity diagram

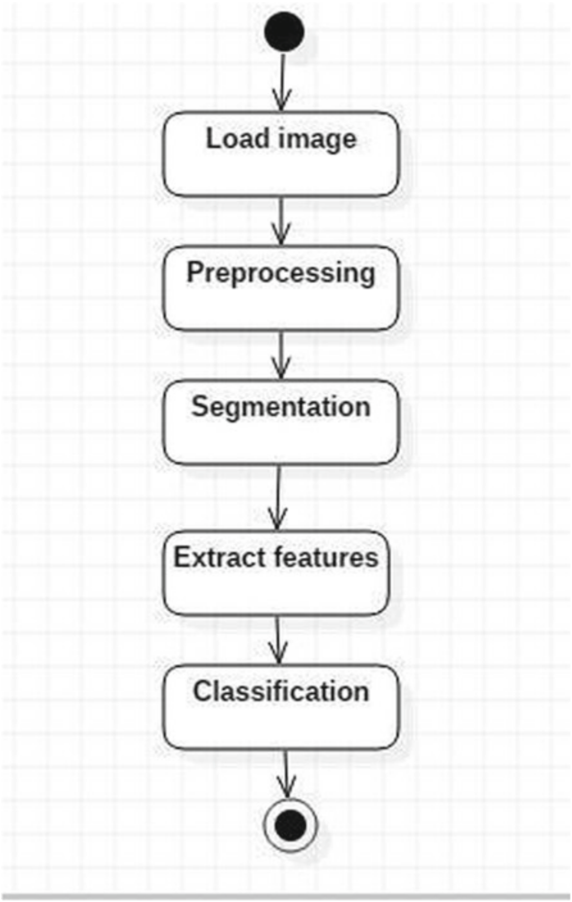


Fig. 5 Extraction of blood vessels (morphological operations applied)

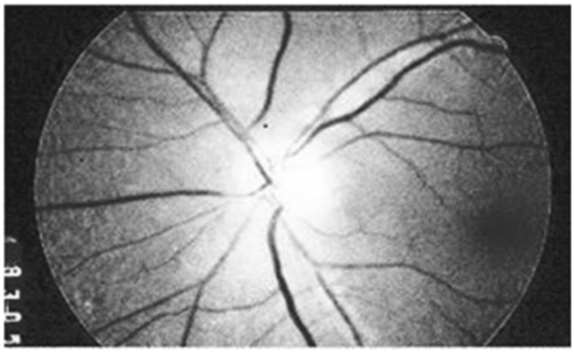

**Fig. 6** Extraction of microaneurysms (disc-based dilation operation is applied)

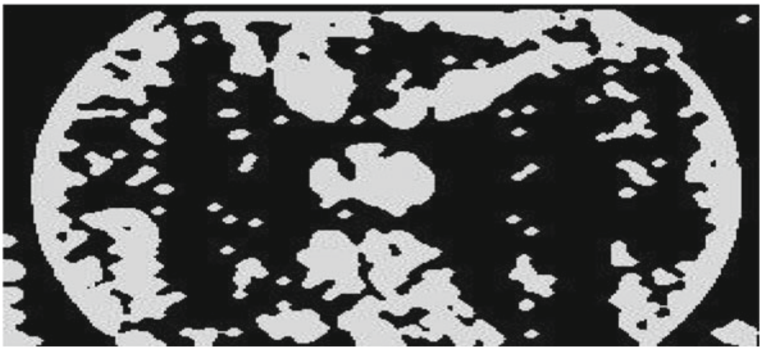

**Fig. 7** Extraction of exudates (conversion from RGB to CMY and binarization operation)

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