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# Automatic Detection of Abnormalities of Diabetic Retinopathy Images

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**Abstract –** *At present, Diabetic Retinopathy (DR) was one of the main cause of blindness for diabetic patients. The diabetic retinopathy was caused due to some abnormalities present in the retina of the eye. The abnormalities may be Microaneurysms (MAs), Oxydates, Haemorrhages. It causes swelling of blood vessels or Bursting of blood vessels in retina. The DR can be controlled by identifying it at earlier stages. For this ophthalmologists will supervise the retinal images obtained by using color fundus camera. This requires ophthalmologists to spend more amount of time & energy. It also requires to store all the normal & abnormal images, which increases the space required. So to avoid all these difficulties a new method is proposed in this paper for detecting all abnormalities from the retinal images. The abnormalities are detected by applying a series of operations. It includes preprocessing, Morphological operations, feature extraction & classification. The classifier used is Support Vector Machine (SVM). It improves overall performance & gives result with an average accuracy of 91%.*

***Key Words*:**
Diabetic Retinopathy (DR), Microaneurysms (MA's), Exudates, Haemorrhages, Morphology, Support Vector Machine(SVM).

## 1.INTRODUCTION

Diabetic Retinopathy (DR) is the most common diabetic eye disease and a leading cause of blindness in adults [1], [5]. This disease causes abnormalities in blood vessels of retina. There are also chances of causing swelling & leakage of fluid from blood vessel [2]. Diabetic Retinopathy can be noticed at initial stages which causes some changes in vision. But if it do not get treatment at initial stages DR can get worst & finally causes vision loss permanently. World Health Organization(WHO) has estimated that Dr is responsible for 4.8% of 37 million cases of blindness in the world. In [1], Akara Sopharak investigated a set of optimally adjusted morphological operators to detect microaneurysms from nondialated pupil & low contrast images. He detected the various abnormalities & graded them. The sensitivity and specificity are rated as 81.66% and 99.99%. In [2] Alan D Fleming showed that how image normalization can be improved to detect Microaneurysms & other dots on the images. The specificity & sensitivity are given as 85.4% and 83.1% respectively. In [15], Chin-Wei Hsu compared the method of multiclass SVM & provided implementation for 2 such "all-together" method. After that their performance was compared with 3 methods based on binary classification, one-against-all, one-against-one and DAGSVM. The rest of the paper contains following- retinal abnormalities, preprocessing & feature extraction, details of SVM classifier & results of classifier.

## 2. RETINAL ABNORMALITIES

Following are the commom abnormalities found in retina.

### 2.1 Microaneurysms

It is a swelling that is formed on tiny blood vessels [4]. It may break & allow blood to leak out in tisssues.It is the earliest visibility of DR in diabetic patients[4].

### 2.2 Haemorrhages

It is a eye disorder in which bleeding occurs in the retina[6]. It takes place outside the macula if not detected over long time. It may cause severe impairment of vision[9].

### 2.3 Exudates

Exudates are random yellowish or whitish patches of various sizes, shapes & at different locations[5]. It originates when DR progress causing, a fluid rich in protein and cellular elements that comes out of blood vessel due to inflammation & deposited in near by tissue[1]. It is the visible sign of DR & major cause of visual loss.

The various abnormalities found in retina is shown in Fig.1

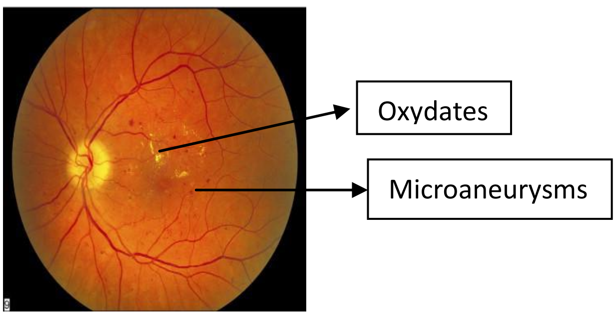



**Fig. 1** Abnormal retinal Image

## 3. PROPOSED METHOD

The main aim of this paper is to detect DR at its early stage. The image of the retina is subjected to various preprocessing steps containing green channel extraction, contrast enhancement , median filter & histogram equalization.After preprocessing, the image is morphologically operated by a disk shaped structuring element [1]. Connected component analysis method is used for the removal of optic disk [10]. This image is then utilized for feature extraction. The features like microaneurysms area, homogeneity and texture properties are extracted [6], [7]. The appropriate features for classification are selected. Support Vector Machine technique is used for classifying the input images as normal and DR based image as well as detecting the earlier stage of DR using the extracted features [9].

### 3.1 Image Acquisition

The proposed methodology is given in fig.-1. In this method, a dataset of manually labeled images is taken. This consist of 105 images taken from screening program for DR in Lotus Eye Care Hospital, Coimbatore. The images were acquired using cannon non-mydriatic ZEISS camera. Each image is 24 bit per pixel at a resolution of 774 x 893 in JPEG format. Of the 105 images in dataset, 95 are of patients with abnormal (contains microaneurysms) & rest of images are normal.

### 3.2 Preprocessing

Pre-processing is the initial step in all the case of image related diagnosis system & it helps in accurate feature extraction. In case of Diabetic Retinopathy, the retinal images in the dataset are often noisy & poorly illuminated because of unknown noise and camera settings. Also the color of retina has wide variation from patient to patient. Thus to remove noise & undesired region the images are subjected to preprocessing steps, which include green channel extraction, histogram equalization and contrast enhancement.

### 3.2.1 Green Channel Extraction

In green channel of color images, MAs appear as dark patterns, small, isolated and of circular shape. The Green channel is the most contrasted one, that red channel is saturated &blue channel does not contain any information [3]. Green light is less absorbrd by fundus layers that blue part of spectrum, but more than red light , which penetrates deeper into the layers of inner eye and which is mainly reflected in the choroid. The red light is less absorbed by pigments of inner eye, and it dominates reflected spectrum. This is the reason why color fundus images appear reddish. Because of lower absorption coefficient for red light, structures containing pigments are less contrasted than green light. This does not mean that there cannot be any useful information in red & blue channel. It just mean that blood containing elements in retinal layer are best represented and have highest contrast in the green channel.

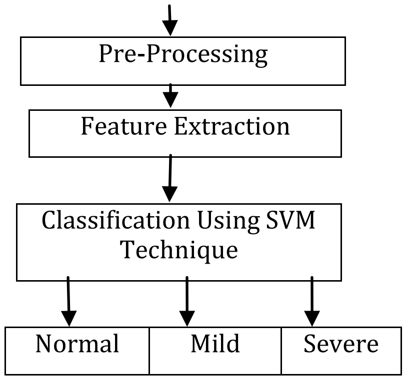



**Fig. 2** Proposed Methodology

### 3.2.2 Histogram Equilization

It is defined as the process of adjusting intensity values of the images [3]. Here contrast-limited adaptive histogram equalization (CLAHE) is performed. Unlike histogram equalization, it operates on small data regions (tiles) rather than entire image. Each tile's contrast is enhanced so that histogram of each output region approximately matches the specified histogram. The contrast enhancement can be limited in order to avoid amplification of noise which might be present in image [1]

### 3.2.3 Filtering

The necessity of filtering the histogram equalized image is to suppress the background pixels along the microaneurysms pixels.
Here a 3 x 3 median filter is used to remove the poor illuminated pixels [3].

Colour Fundus

Retinal Image

### 3.2.4 Contrast Enhancement

It is essential to distinguish the MAs from blood vessel & background of the images [2]. For this purpose, Contrast enhancement step is used in preprocessing to enhance contrast of microaneurysms. This process facilitates the image for further processing.

### 3.2.5 Morphological Operation

The contrast enhanced image is then converted into binary image by applying proper thresholding value. This binary image is subjected to morphological operations i.e. opening & closing [1]. Closing operation is defined as dialation& opening operation is defined as erosion. Dialation is an operation that grows or thickens objects in a binary image. Erosion shrinks or thins the object[3]. Structuring element is defined as the shape ( dimension) that controls the process of thickening and thinning.

### 3.2.6 Optic Disk Elimination

Optic Disk occupies more area of retinal image and it should be removed for facilitating MAs detection. Thus the connected component analysis method is used for the elimination of optic disk [10]
The various preprocessing steps are shown in fig-2.

### 3.3 Feature Extraction

The preprocessed image after removal of optic disk & blood vessel contains only MAs. This image is used for feature extraction [6]. The statistical features extracted are MAs area, entropy, correlation, energy, contrast, homogeneity, standard deviation mean [5]. From these extracted features, effective features are selected for SVM classification.

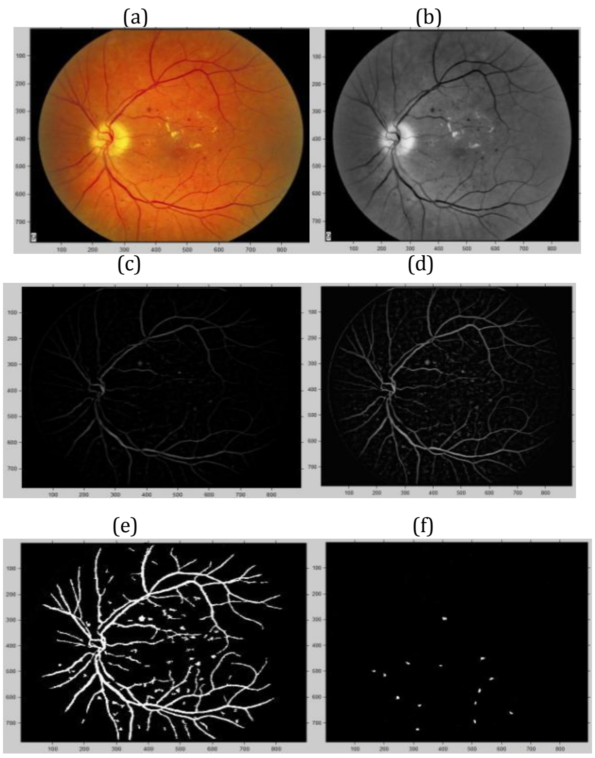
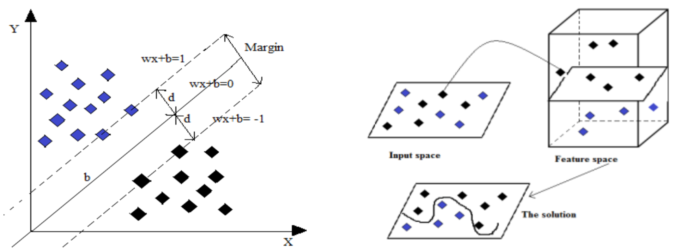



**Fig. 3:** (a) RGB image with MAs, (b) Green channel of MAs image,(c) Filtered MAs image, (d) Histogram equilized image, (e) Image with MAs and blood vessel, (f) Image with MA's

## 4. SVM CLASSIFIER

It is a supervised learning process applied for analyzing training data to find an optimal way to classify diabetic retinopathy images into their respective classes namely Normal, Mild and Severe. SVM is a robust method used for data classification and regression. The SVM Methods are described in detail by Vapnik [13]. It construct a hyperplane for separating the given data linearly into separate classes (Fig.3 a). The classification parameters formed according to the calculated features using SVM algorithm. For nonlinear classification of given data, SVM uses non-linear kernel function to map the given data into high dimensional feature space where given data can be linearly classified & is shown in Fig.4 (b). Kernel Function K (x,y) represents inner product {*Φ(x)*,*Φ*(y)} in feature space.




(a) Linear Classification (b) Nonlinear Classification

**Fig. 4 SVM Classifier**

In this case, RBF kernel function is used as

$$K(x,x')=\exp\left\{\frac{-||x-x'||^2}{2\sigma^2}\right\}$$

Where x & x′ are training vectors, where σ is parameter that controls the width of Gaussian.

## 5. EXPERIMENTAL RESULTS

The features like MAs area, entropy, contrast , etc are obtained from preprocessed image & are provided as input to SVM Classifier. The implementation of this technique is carried out using Matlab. The result of classification procedure are given in Table -1. The sensitivity ,specificity and accuracy values are calculated using formulas.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \text{ ------------- } (1)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \text{ ------------ } (2)$$

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \text{ ---------}(3)$$

**Table -1:** Results of SVM Clasifier

| MODEL | TP | TN | FP | FN |
|---|---|---|---|---|
| SVM | 23 | 4 | 1 | 2 |

**Table -2:** Results of Sensitivity, Specificity, Accuracy

| Model | Sensitivity | Specificity | Accuracy |
|---|---|---|---|
| SVM | 92 | 80 | 90 |

## 6. CONCLUSION

The main aim of this work is to reduce the ophthalmologists work in screening theDR based on Microaneurysms using SVM classifier.The retinal images are subjected to gray scale conversion, preprocessing and feature extraction steps.The SVM classifier classifies images as Normal, Mild and Severe based on the extracted features as input. TheSensitivity and specificity are 92% and 80% respectively. Thus this SVM technique has given a successful DR screening method which helps to detect the disease in early stage.

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