

# Detection and classification of Diabetic Retinopathy in Retinal Images using ANN

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## ABSTRACT

Diabetic retinopathy is a Complication of diabetes that causes vision loss if it is not recognized and treated timely. It is characterized by the changes in blood vessels and abnormalities in macular region. To detect these abnormalities manually, ophthalmologists perform pupil dilation which irritates patient eye. To overcome this drawback, image processing technique is used in diabetic retinopathy. And a completely automated system is presented in this paper for the detection and classification of diabetic retinopathy. This paper focuses on Artificial Neural Network (ANN) to detect diabetic retinopathy in retinal fundus images. To develop this proposed system, a detection of micro-aneurysms, exudates and blood vessels is done from retinal fundus images. GLCM is formed using MATLAB function and several features like entropy, homogeneity, area of micro-aneurysms, exudates and blood vessels act as input to ANN. ANN is used to classify retinal images as mild, moderate and higher cases of diabetic retinopathy. In order to classify the DR images, different classes are represented using relevant and significant features.

**Keywords:** Diabetic Retinopathy (DR), fundus image, microaneurysms, exudates, image processing, Optic Disc, Artificial Neural Networks.

## I. INTRODUCTION

Diabetic retinopathy is the deterioration of retinal blood vessel which is caused by the complication of diabetes and it can eventually lead to blindness. The longer the patient has diabetes the higher are the chances of developing diabetic retinopathy. It is one of the most common eye diseases which could affects 85 percents of the patients who have had diabetes for 10 years or more. Diabetic retinopathy is characterized by the development of retinal microaneurysms, hemorrhages and exudates.

One of the stages in diabetic retinopathy is Non-Proliferative Diabetic Retinopathy (NPDR), which in this stage, the proliferative of blood vessels does not occur. Lesions of diabetic retinopathy consist of dark and bright lesions. The dark lesions comprise of micro aneurysms and haemorrhages, and the bright lesions include exudates which are yellow deposits of lipid and protein that leak from the capillaries.

There are two levels of diabetic retinopathy namely NPDR and PDR. Nonproliferative diabetic retinopathy is the early stage of diabetic retinopathy, and if the patient's blood sugar is uncontrolled it will be rise to proliferative diabetic retinopathy. Nonproliferative diabetic retinopathy (NPDR) consists of three levels which are mild, moderate, and severe NPDR. Digital retinal images which are used for automated detection of DR contain blood vessels, optic disc, macula and fovea as main components. Any changes in structure of retina or blood vessel is a sign of abnormality so these main components can be used to highlight the presence of any lesion in retina .Many approaches are proposed by the authors to automate and detect the presence of diabetic retinopathy in fundus image. Retinal lesions are used to evaluate different stages and the severity of the diabetic retinopathy. Doctors recognize diabetic retinopathy by examining the features, such as blood vessel area, exudates, hemorrhages, micro aneurysms and texture.

There will always exist differences in the backgrounds and education of human screeners, which causes dispersion in their diagnose making. The physician may

make different diagnoses in different screening times due to human factors, such as tiredness or sickness. High examination time taken for the complete classification of the image when examination part is handled by physician though the screening is done through the computer. A computer-based screening system does not have to be perfect to be used in screening. It is better to use a computer-based screening system for classifying only clearly normal funduses as normal, whereas abnormal and obscure funduses are delivered to a human expert for further classification.

One out of three diabetic patients has signs of DR and one out of ten suffers from its most severe form. As DR does not show any symptoms in its beginning, so the patients do not undergo any eye examination until it is already too late for an optimal treatment and severe retinal damages have been caused. Regular eye fundus examinations for diabetic patients guarantee an early detection of DR which in turn can reduce the incidence of blindness in patients. If diagnosed early, DR can be effectively managed using available treatments. But there are a large number of patients, so to lessen the workload of ophthalmologists an automated detection system is presented.

This paper focuses on these problems described above and an automated algorithm is designed to run on the fundus image and process it for the detection of micro-aneurysms, blood vessels and exudates in an automated manner reducing the burden of the physician and reducing examination time. The overall detection results of micro aneurysms and exudates will be used as baseline of no proliferative diabetic retinopathy (NPDR) classification.

## II. METHODS AND MATERIAL

### A. Ease of Use

#### 1) Pre-processing

All the images were resized to  $720 \times 576$  pixels while preserving the original aspect ratio. Color fundus image is first converted into a gray-scale/green-channel image in order to facilitate the blood vessels segmentation and to decrease the computational time. Gray-scale image provides only the luminance information from the color

image after eliminating the hue and saturation, while the green-channel image provides maximum local contrast between the background and foreground.

### 2) Blood Vessel Extraction

Initially, the green component is extracted from color fundus image and its intensity is inverted. Green channel gives the best contrast between the surface area and blood vessels. Also in inverted green channel, blood vessels appear lighter than background.

1. Intensity Inversion of Green Channel Image
2. Contrast Limited Adaptive Histogram Equalization (Clahe)
3. Morphological Opening Using Ball-Shaped Structuring Element
4. Subtraction of Output Image Of Step4 From Step3 to Remove Optic Disc
5. Binarisation of Optic Disk Removed Image
6. Area Opening Function Applied to Remove Noise
7. Blood Vessels Image With Noise
8. Border Formation Using Method 1 or 2 Using Grayscale Image
9. Creation of Optical Disk Mask Using Grayscale Image
10. Clahe on Green Component Image Followed By Area Opening
11. Addition of Output Image Of Step10 With The Optic Dick Mask
12. Using Logical and for both Output Images of Step7 and Step11 to Get Blood Vessel Extracted Image

### B. Algorithm for Blood Vessel Detection

Contrast limited adaptive histogram equalization (CLAHE) is done to enhance the contrast of the fundus image. The optic disc usually appears as a bright yellow disc-like object on the retina. The optic disc can give false recognition as it looks very similar to a bright lesion thus it is necessary to remove it. If its position is known, any bright lesion candidates on the optic disc can be masked out.

Morphological opening which consists of erosion followed by dilation is applied. Erosion protects blood vessels by reducing their size while dilation blows up

the larger remaining details which are intended to be removed. The image is then subtracted from the adaptive histogram equalized image to remove optic disc. The subtracted image the image is converted from to binary image and using area opening functions smaller pixels (noise) are removed.

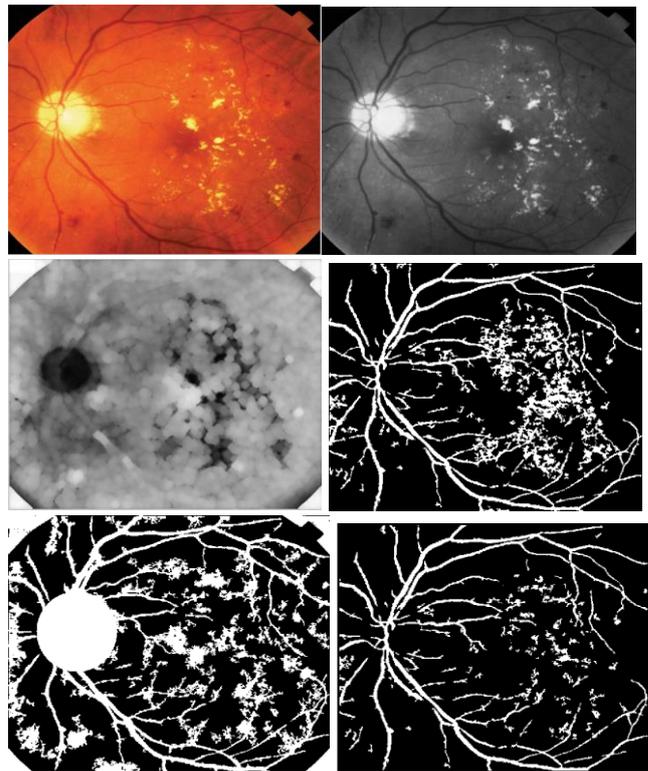
Grayscale image is used for border detection. Canny edge detection to detect the edges before enclosing the circular region with a top and bottom bar. Function “infill” is then applied to fill holes of the image. The circular border is obtained after subtraction of the dilated image with the eroded image.

When a noisy image is obtained the second Method gets activated. This method the intensity of the image is inverses first before image segmentation is applied with the function “im2bw”. The circular region is filled as a result and the circular border is obtained after subtraction of dilated image with the eroded image. For Optic disk masking first the maximum value for each of the 720 columns of the image is found at and then from that the largest value is extracted. The median of coordinates of all brightest points are then obtained. After locating the optical disk, a mask needs to be created.

The function “mesh grid” is to generate x and y matrices while the equation for drawing circle is used to create the mask. H and K are the coordinates (row and column) and R is the Radius.

$$R^2=(x-h)^2+(y-k)^2$$

Then the optic disk masked image with blood vessels is obtained. Two methods of detecting the blood vessels are used. The green channel masked image and grayscale masked image undergo logical AND to give output image and hence by computing their similarity, the non-blood vessels area could be filtered. AND logic is applied to mark out the similar pixels of the two images. The output pixel is registered as binary 1 (white) when the both images’ pixels are binary 1 (white). The obtained image is being a clear blood vessels image. The area of the blood vessels is obtained by using two loops to count the number of pixels with binary 1 in the final blood vessel extracted image.



**Figure 1.** a)original image b)green component image c)image after imerode and imdilate d) blood vessels with noise e)blood vessel and noise with mask f)final blood vessel image

## 1. Bright Lesion Detection

- 1) Contrast Enhancement of Grassdale Image
- 2) Age Detection Using Canny Edge Detector
- 3) Filling Of Holes
- 4) Border Formation
- 5) Applying Column Filter
- 6) Image Segmentation
- 7) Detection of Optic Disc
- 8) Creation of Optic Disc Mask
- 9) Removal of Border
- 10) Morphological Closing to Get Region with Exudates
- 11) Blood Vessels Removal Extraction of Dark Features
- 12) Optic Disc and Border Removal
- 13) Identification of Dark Feature
- 14) Removal of Dark Feature
- 15) Logical and Of Output of Step14 and Step 10 to Get Final Image

## 2. Exudate Segmentation Algorithm

Exudates are yellow lesions of various shapes and size with relatively distinct margins. As the disease progress, more lesions like exudates appear in retina. The exudates are detected after removal of the border, optic disk and non-exudate area. Contrast enhancement of rescale image is done.

The morphological closing operation is performed to remove the blood vessels. Dilation expands the exudates area while erosion removes the blood vessels. Column filter is applied on the image. This image is converted to binary using the function “im2bw” with a threshold value to filter out the exudates.

The canny edge detector is used to detect the edges .Border formation is done using method 1 or 2 as described earlier. Edges are found using canny method; before removing the circular border to fill the enclosed small area.

The location of the optical disk is detected by the brightest points on the gray scale image. It is usually the maximum value and then a circular mask is then created to cover it. The regions of the exudates are obtained after the removal of the circular border. Morphological closing is then applied to the image. The dilation function is to fill the exudates while erosion expands their sizes.

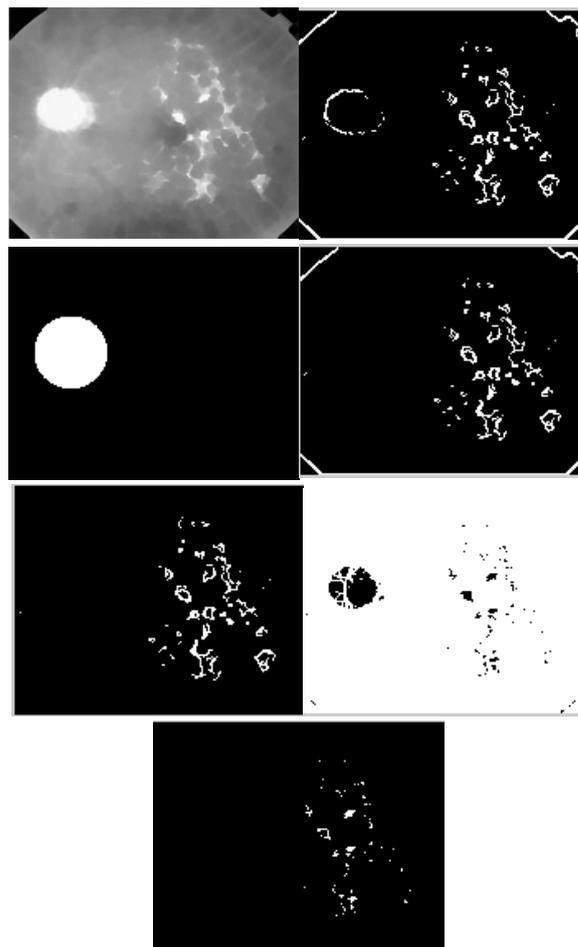
Non-exudates (dark features) are extracted from the gray scale image using function “im2bw” and are represented as binary 1 (white) after intensity inversion. Then the circular border, edges and the large areas are removed. Being the bright spots on the image, contrast limited adaptive histogram equalization is applied twice followed by image segmentation to make the exudates visible.

AND logic is used for removal of noise for the detection of exudates. Regions with exudates are marked out after applying column filter but this includes non-exudates such as hemorrhages and has to be removed as noise.

By removing the non-exudates from the detected area, exudates can be obtained. Image segmentation is applied to the gray scale image to extract the bright spots for comparison. These areas (bright features) are

represented as black whereas dark features are represented as white.

By applying AND logic to Expanded exudates region image obtained After Morphological closing and image with Dark features represented as white, the non-exudates regions are set to set to black and removed when the pixels for both images are binary 1 . Hence the exudates are detected. The area of the exudates is calculated by using two loops for counting the number of pixels with binary 1 in the final exudate image.



**Figure 2.** a) gray scale image b) image after blood vessel removal c) Image after segmentation d) mask for optic disc e) image with optic disc removed f) region with exudates g) dark features h) exudates after and function

## 3. Micro aneurysm Detection

Micro aneurysms are the earliest clinical sign of diabetic retinopathy .They occur because of swelling of retinal capillaries in the eye of human. They appear as dark red dots either remains as cluster or isolated spots in the

retina of human eye. The severity in micro aneurysms may cause haemorrhages which are seen like blood clot in retina. Micro aneurysms are red in colour with a diameter less than 125 are.

This part is in progress to recognize hemorrhages and micro aneurysms (IIMA). Micro aneurysms are first clinically detectable lesions of diabetic retinopathy. The lesions are of same color as blood vessels and very similar in color to the fundus background.

The gray scale image is used for creation of circular border and mask for optic disk. First the green component image is used to find edges using canny edge detection method; before removing the circular border to fill the enclosed small area. Adaptive histogram equalization is applied twice followed by image segmentation to make the bright lesions visible.

Resulting bright feature areas undergo comparison using AND logic with large area removed image for exudates removal. Then the blood vessels and optic disk are eliminated to give the micro aneurysm alone. Because of better efficiency gray scale image is used in place of the green channel image for detection of border. The method uses canny edge detection to detect the edges. The circular region is then clathrated with a top and bottom bar. the region is filled by Use of the function “imfill” When the image obtained after dilation is subtracted with the eroded image the circular border is formed. The creation of mask for optic disk is done using grayscale image. using loops to locate the largest value will be ineffective because optic disk is made up of a group of bright spots. At the beginning the maximum value for each of the columns of the image is determined before calculating the largest value. Then coordinates of all brightest points are found and median is taken in case of multiple points. USING these coordinates the circular mask is drawn.

Step 1 Contrast enhancement of intensity grayscale image Green component image undergoes adaptive histogram equalization twice

Step 2 Canny edge detection on contrast adjusted grayscale image. Imfill function to fill the holes in grayscale image Erosion followed by dilation Subtraction of dilated image with eroded image to form circular border.

Step 3 If noisy image is obtained instead of border then complement the grayscale image and repeat the above step to find new border.

Step 4 circular border is removed before applying the function “imfill” to fill the circumscribed area.

Step 5 The holes (microaneurysms with noise) image is obtained by subtracting away the edges image and removing the larger area image using function “bwareaopen”.

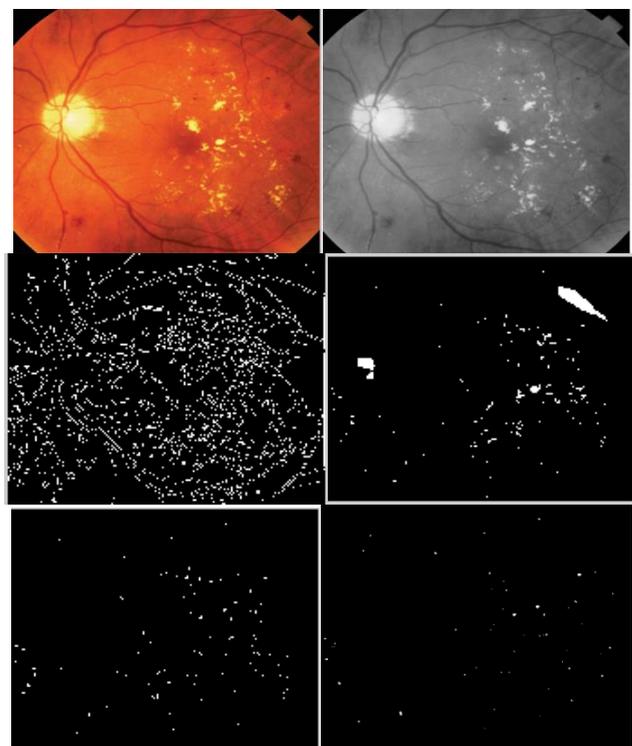
Step 6 the image is applied with adaptive histogram equalization is used twice on the image and image segmentation is done to make the exudates visible .

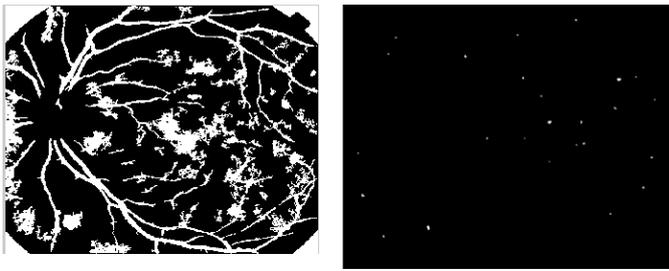
Step 7 The bright features are compared with Step 5 outcome using AND logic to remove the exudates.

Step 8 Blood vessels are extracted by applying adaptive histogram equalization twice and image segmentation using another threshold value. A clearer image of blood vessels is acquired after removing the small area of noise.

Step 9 This image is compared using AND logic with the result from the Step 7 to remove the vessels

Step 10 The final microaneurysms image is obtained after removal of noise and optic disk area.





**Figure 3.** a)Original image b)grayscale image c)edges w/o circular border d)imfilled area e)microaneurysms with noise f)area of microaneurysms after removal of exudates g) blood vessels/noise without small area h) microaneurysm

### III. RESULTS AND DISCUSSION

#### Feature Extraction

After the detection stage fundus images features i.e., area of blood vessels, area of exudates, and area of microaneurysms are extracted along with texture properties. These properties are later used for classification of the images .

1) *Texture analysis:* The function of spatial variation in pixel intensities (gray value) is known as image texture. The basic types of texture analysis computation are structural, statistical and spectral. The texture features considered for this work are entropy and homogeneity. Cooccurrence matrix captures the spatial distribution of gray level from which homogeneity can be obtained.

Entropy is a statistical measure of the disorder or randomness in a grayscale image GLCM is created by calculating how often a pixel with gray level value  $i$  occurs in a specific spatial relationship to a pixel with the value  $j$ . It returns a value between 0 and 1.

There are now total of 7 features which include two area calculations (exudates and blood vessels) and five texture features.

Texture is a measure of properties such as smoothness, coarseness, and regularity of pixels in an image. Texture can also be defined as a mutual relationship among intensity values of neighboring pixels repeated over an area larger than the size of the relationship. Conventional texture recognition system can be grouped into three classes: structural, statistical and spectral.

Structural texture analysis is more complex as compared to the statistical approach. Structural is the arrangement of texture elements while spectral is the analysis based in spatial frequency domain. Statistical is based on the intensity relationship of the pixels in statistical features like co-occurrence matrix. Statistical algorithms are based on the relationship between intensity values of pixels; measures include entropy, contrast, and correlation based on the gray level.

Two texture properties of the image are calculated. Entropy is determined by applying histogram equalization to the green channel of the image while homogeneity is calculated by using Gray-Level Co-occurrence Matrix on the grayscale image. Entropy is a texture analysis function in the MATLAB Image Processing Toolbox.

$E = \text{entropy}(I)$  returns  $E$ , a scalar value representing the entropy of grayscale image  $I$ . Entropy is a statistical measure of randomness that characterizes the texture of the input image. Entropy is define d as

$$\text{sum}(p.*\log_2(p))$$

where  $p$  contains the histogram counts .

The function “entropy” is then used on the image which gives a scalar value. This represents the entropy of the intensity for the fundus image.

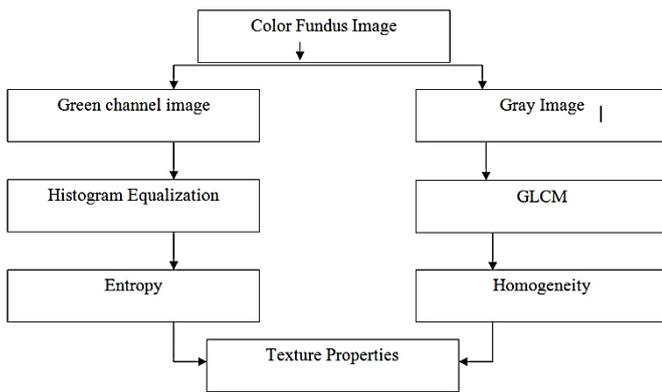
Grey Level Co-occurrence Matrix (GLCM) is the computation of the frequency of each pixel pair occurring for different combinations of pixel brightness values in an image. `graycomatrix (I)` creates a gray-level co-occurrence matrix (GLCM) or gray level spatial dependence matrix. from image  $I$ .

`graycoprops` function calculates the properties from the gray-level co-occurrence matrix `glcm`. `glcm` is an  $m$ -by- $n$ -by- $p$  array of valid gray-level co-occurrence matrices. `graycoprops` normalizes the gray-level co-occurrence matrix (GLCM) so that the sum of its elements is equal to 1. Each element  $(r,c)$  in the normalized GLCM is the joint probability occurrence of pixel pairs with a defined spatial relationship having gray level values  $r$  and  $c$  in the image. `Graycoprops` uses the normalized GLCM to calculate properties.

Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

The homogeneity is the measurement of the closeness of the distribution of elements in the Grey Level co-occurrence Matrix (GLCM) to the GLCM diagonal, and returns a value between 0 and 1. The homogeneity formula is as follows:

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$



**Figure 4.** Block Diagram for the Texture Properties

### Classification

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. NNs are composed of multiple nodes, which imitate biological neurons of human brain. The neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value.

Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values. There are two Artificial Neural Network topologies FeedForward and Feedback. The ANN used here is a feed-forward ANN using back propagation algorithm and uses supervised learning to train the neural network. Supervised learning is a machine learning algorithm which uses a known dataset (called the training dataset) to make the predictions. The training dataset includes

input data and output values. From it, the supervised learning algorithm seeks to build a model that can make predictions of the response values for a new dataset. A test dataset is used for model validation.

The input layer is made up of input nodes to accept the feature values while the subsequent layers process the values using activation function. There are 10 neurons for each “hidden layer” and the trained network would give output as binary numbers which represent the three different levels of diabetic retinopathy.

The input data is normalized to the range between 0 and 1 to balance the weight of the neurons in the ANN. The different classes are defined as binary numbers as shown in the table below.

**Table 1.** Representation of different classes

Classes	Binary Representation
Normal	00
Mild stage	01
Higher stage	10

The testing data would only contain input data values as the output stages are to be determined by ANN. The training data is created using 25 images from the DIATERBO dataset .FOR any input image AREA IS CALCULATED for exudates, micro-aneurysm and blood vessels and based on that entropy and homogeneity calculated and this act as input to ANN which classifies the input image to any one of the class .

### IV. CONCLUSION

Thus an automated system is proposed for the detection of micro aneurysms, exudates and blood vessels by using morphological process using MATLAB code in this paper. Since it is an automated process earlier lesion detection is possible and this analysis is used to estimate the severity of diabetic retinopathy which may reduce the probability of partial or complete vision loss. Diabetic retinopathy is present in nearly all persons who have had diabetes eventually suffer.

Diabetic Retinopathy (DR) is the complex micro vascular complications of diabetes and the main cause of blindness. DR lesions are divided into dark and

bright lesions where dark lesions appear in the initial level of the disease.

Early detection of dark lesions is prominent for controlling the disease and avoiding suddenly loss vision. At the other hand, manually evaluating of retinal images is time consuming and contains errors. Therefore, designing automatic detection systems is critical.

In this paper, several approaches that are used for pre-processing retinal images for the purpose of dark lesion and bright lesion detection are summarized. Finally the data is analysed by ANN (Artificial neural network) which classifies the fundus image as normal, mild or severe case of diabetic retinopathy.

### **Enhancement**

This paper deals with the detection of micro aneurysms, exudates and blood vessels and later enhancement is the detection of haemorrhages which is also a type of red lesion which is caused due to clotting of blood vessels. It occurs in deeper layers of retina. It is also called 'blot' haemorrhages and occurs as irregular shaped red lesion. Based on the nature and morphological analysis the haemorrhages can also be detected and analysed.

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