

# DETECTION OF DIABETIC RETINOPATHY USING RETINAL FUNDUS IMAGES

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**Abstract**— Diabetic retinopathy is main cause of the vision-loss in adults. The diabetic retinopathy consists of background vessels, retina, fundus images, vessels and non-vessels images. Due to diabetic retinopathy, around 4.2 million of adults had the diabetic retinopathy and 655,000 had the vision-loss, which are maximized every day. It is said to be one of the most common complication of the DM (Diabetes Mellitus). The treatment of diabetic retinopathy is not easy as there is no symptom presented at early phase and patients hardly notice the vision-loss. Most of the people couldn't recognize that they have the diabetic retinopathy until the disease is started to affect their eye that generally occurs in final phase. As an outcome, most of the people might not go via the treatment. Therefore, the scheme of coordinated management is very crucial to address the clinical challenges of the diabetic retinopathy and preventing its development. Early classification and identification of retinal images are being very serious concern to research community. In our proposed system we are going to identify the presence of diabetic retinopathy from retinal fundus images using MATLAB R2013a.

**Keywords**—Diabetic retinopathy, Retinal fundus images, Diabetic Mellitus, MATLAB

## I. INTRODUCTION

According to estimation by The World Health Organisation(WHO), there are 347 million people affected by Diabetes and it predicts that Diabetes will be the seventh major cause of deaths worldwide by 2030. Diabetic Retinopathy(DR) is the most common form of diabetic eye disease. It usually affects people who have diagnosed or un diagnosed diabetes for a significant number of years. Retinopathy can affect all diabetics and increasing the risk of blindness, if it is left untreated. The risk of developing diabetic retinopathy is known to increase with less well controlled

blood sugar as well with age and blood pressure level. DR occurs when changes in the blood glucose levels cause changes in the retinal blood vessels. These blood vessels will swell up and leak fluid into the rear of the eye. In other cases, abnormal blood vessels will grow on the surface of the retina. DR can gradually become more serious and can lead to blindness, unless treated.

The main stages of this disease are non-proliferative and proliferative retinopathy. DR can be categorized as Microaneurysm, Haemorrhages and red lesions like hard exudates, soft exudates and veins. The early stage of this disease is called Microaneurysm(MAs). In this stage, the blood vessels may become swell or bulge(aneurysm). The swelling in the retina is caused by the leakage of fluid by the blood vessels. This condition is called macular edema, and it changes the vision of the individuals with the disease. The blurriness is similar to trying to look through water. The retina consists of fluid deposits that may clear up on their own, but fatty deposits in the retina sometimes remain that can have an effect on vision. In many instances when the small blood vessels close down, new, unhealthy blood vessels can grow. These unhealthy blood vessels are unfit to feed the retina. This stage is called proliferative diabetic retinopathy.

The fundus image of the retina can be obtained from the fundus camera are often imperfect, normally in low contrast and blurry. The accurate diagnosing of DR is a very difficult task for the several reasons: 1) the presence of lesions, exudates, haemorrhages; 2) the variability of the blood vessel width and length; 3) the low contrast between the vessels and the background; 4) the central reflex on large vessels; 5) the presence of small regions affected by noise; and 6) the conclusion between vessels. Sample of fundus images are shown in Figure 1.



(a)Normal (b)DR

Fig 1. Fundus Image

In order to improve the reliability of diagnosis, several previous studies have been developed automatic and semi-automatic diagnosis of medical images using Masking algorithm and SVM classifiers.

## II. RELATED WORK

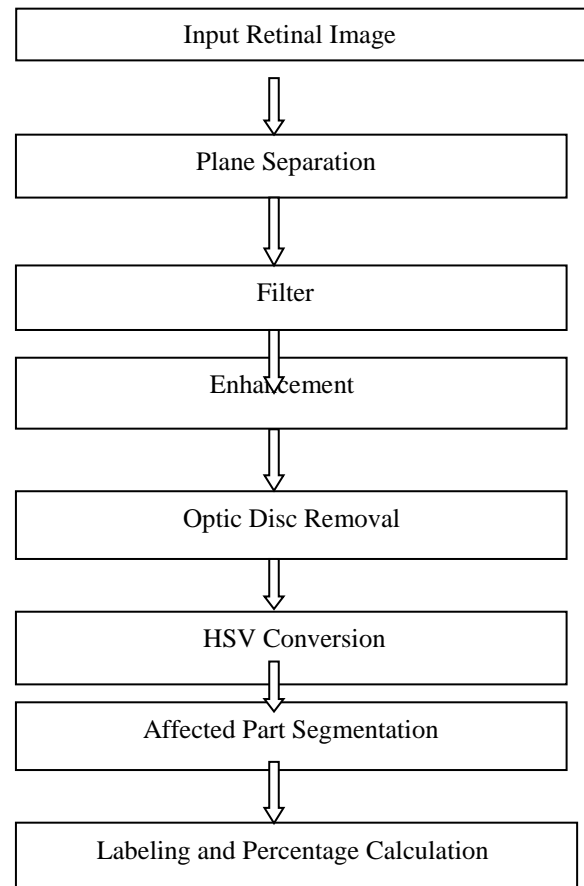
Most of the researches have focused on the automatic detection of Diabetic Retinopathy from the retinal fundus images. In existing, they have analyzed MA detect ability using small 25 by 25 pixel patches extracted from fundus images. Raw pixel intensities of extracted patches served directly as inputs into the following classifiers: a random forest(RF) and an automatic neural network(ANN).

They have explored the use of two techniques(principal component analysis and random forest feature importance) for reducing the input dimensionality. This techniques involves too many process and the principal components will be biased towards features with high variance, leading to false results.

The sensitivity or specificity of the existing algorithm for the detection of diabetic retinopathy is not sufficient enough to be used for medical applications. The shape and location of the presence of diabetic retinopathy in retinal fundus images is very unpredictable. The red lesions can be found in the macula, overlapping in the blood vessels or near the optic disc. Also, the shape of the lesions is not determined.

## III. PROPOSED METHOD

In our proposed system, firstly retinal fundus image (RGB) will be used. Then that will be preprocessed. Preprocessing consists of plane separation, filtering, enhancement. Then by using masking algorithm and HSV intensity values retinal image is segmented to detect affected part. Then labeling and affected percentage calculation will be performed. The workflow of our proposed system is as follows:

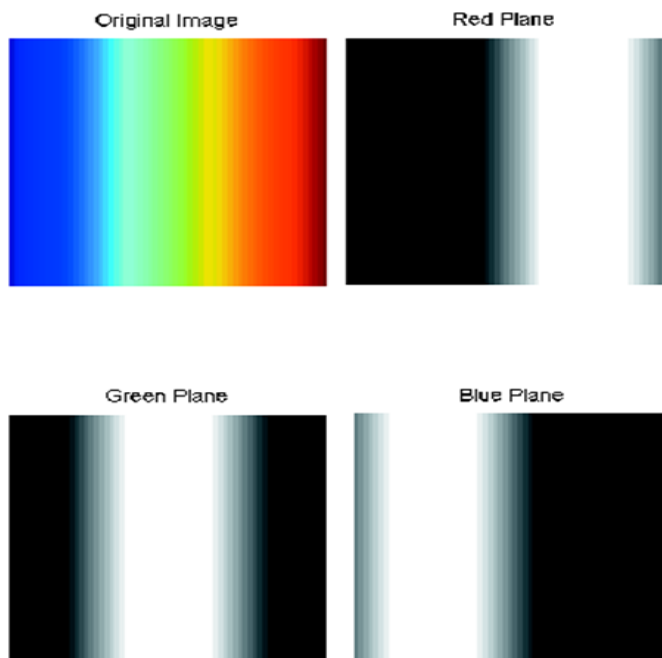


(a) INPUT IMAGE- RGB COLOR MODEL

An RGB image, sometimes referred to as a *true color* image, is stored in MATLAB as an m-by-n-by-3 data array that defines red, green, and blue color components for each individual pixel. RGB images do not use a palette. At the pixel's location, the color of each pixel is determined by the combination of the red, green, and blue intensities stored in each color plane. Graphics file formats store RGB images as 24-bit images, where the red, green, and blue components are 8 bits each. This yields a potential of 16 million colors. The precision with which a real-life image can be replicated has led to the commonly used term true color image. The RGB color model is an additive color model in which red, green and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. The main purpose of the RGB color model is for the sensing, representation and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB color model already had a solid theory behind it, based in human perception of colors.

### (b) PLANE SEPARATION

An RGB MATLAB array can be of class double, uint8, or uint16. In an RGB array of class double, each color component is a value between 0 and 1. A pixel whose color components are (0, 0, 0) displays as black, and a pixel whose color components are (1, 1, 1) displays as white. The three color components for each pixel are stored along the third dimension of the data array. Plane separation is illustrated below.



### (c) FILTER

The ultimate aim of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is known as "window", which slides, entry by entry, over the entire signal. If the window has an odd number of entries, then the median is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median, see median for more details.

The nonlinear digital filtering technique called as median filter, used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to increase the results of later processing. The median filter is an algorithm that is useful for the removal of impulse noise (also known as binary noise), which is manifested in a digital image by corruption of the captured image with bright and dark pixels that randomly appear throughout the spatial distribution. The median filter, when applied to grey scale images, is a neighborhood brightness-ranking algorithm that

works by first placing the brightness values of the pixels from each neighborhood in ascending order. The median or middle value of this ordered sequence is then selected as the representative brightness value for that neighbourhood. Subsequently, each pixel of the filtered image is defined as the median brightness value of its corresponding neighbourhood in the original image. Median filter is used to remove the speckle noise and salt-and-pepper noise (impulsive noise). It preserves the edges of an image than other filters.

### (d) ENHANCEMENT

Image Enhancement is the technique to increase the interpretability or perception of information in images for human viewers. It is to increase the image quality so that the resultant image is better than the original image for a specific application. The main purpose of image enhancement is to bring out detail that is hidden in an image or to improve contrast in a low contrast image. Image enhancement can be done by increasing contrast and removing noise from the image or if image is blurred then we remove blurring also. In addition HE, AHE will also make the medium brightness toward the middle gray level of an image disregarding of the input image, and introduce objectionable artifacts and affected contrast effects. This makes the visual quality of processed imagery inadequate image histograms resembles each other as much as possible. In image acquisition process, if noise is present in the image that will become an error. In result we have an image that does not give the true intensity of the image pixels. The removal of noise from a signal or from an image is called noise reduction process. Conceptually, the signal processing as same as the noise reduction technique. However, the knowledge of input signal is required by which we can find the expected output that is depend on the type of signal. Firstly image captured by the sensor then image goes under different types of smoothing filters after that we have the output or resultant image.

### (e) OPTIC DISC REMOVAL

Optical disc, it is a part in normal human eye which carries 1 to 1.2 million afferent(conducted inwards) nerve fibres from the eye towards the brain. The optical disc occupies huge area of the fundus image and it should be eliminated for easy indication. the optical disc present in RGB fundus images is shiny, yellowish or white colored and almost round in shape. The optical disc removed by giving the grey image as input. After processing, the optical disc part will be white color and the remaining parts will be in black color.

#### (f) HSV CONVERSION

The HSV color wheel is sometimes represented as a cone or cylinder. As hue varies from 0 to 1.0, the corresponding colors vary from red through yellow, green, cyan, blue, magenta, and back to red, so that there are actually red values both at 0 and 1.0. As saturation varies from 0 to 1.0, the corresponding colors (hues) vary from unsaturated (shades of gray) to fully saturated (no white component). As value, or brightness, varies from 0 to 1.0, the corresponding colors become increasingly brighter.

The processing of color vision is done by using RGB color space or HSV color space. RGB color space describes colors in terms of the amount of red, green, and blue present. HSV color space describes colors in terms of the Hue, Saturation, and Value. In situations where color description plays an integral role, the HSV color model is often preferred over the RGB model. The HSV model describes colors similarly to how the human eye tends to perceive color. RGB defines color in terms of a combination of primary colors, whereas, HSV describes color using more familiar comparisons such as color, vibrancy and brightness.

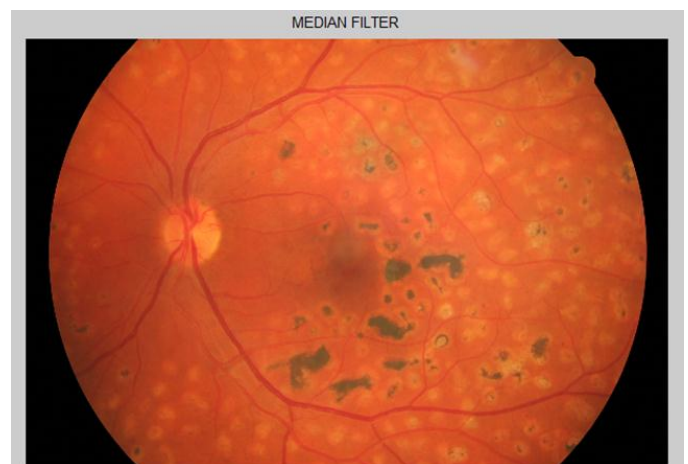
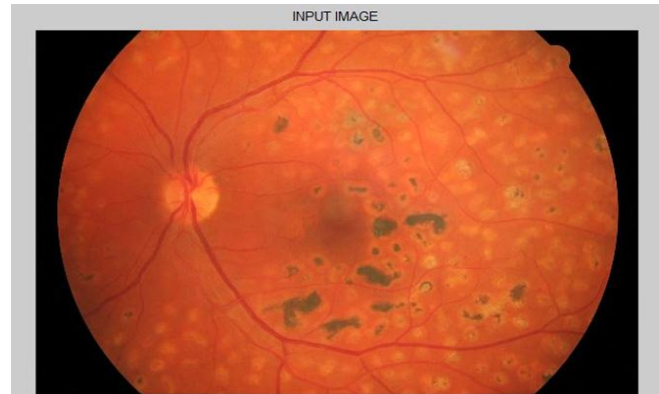
#### (g) SEGMENTATION

Image segmentation is the process of dividing an image into many parts. This is typically used to find out the objects or other relevant information in digital images. The process in which partitioning an image into parts or regions is known as Image Segmentation. This segmentation into parts is often based on the characteristics of the pixels in the image. For example, the way to identify the regions in an image is to look for abrupt discontinuities in pixel values, which typically indicate edges. These edges can define regions. Other methods divide the image into regions based on color values or texture.

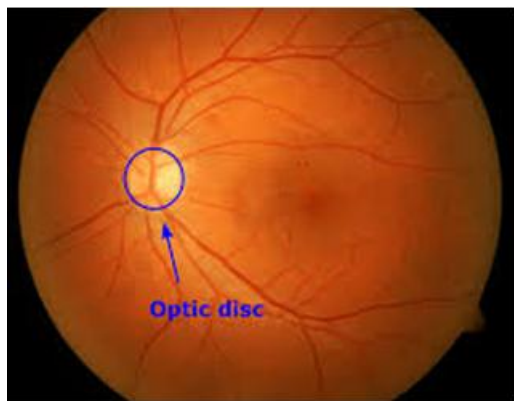
#### (h) PERCENTAGE CALCULATION

Affected percentage will be calculated based on the mathematical formula given below.

$$\text{affected portion(\%)} = \frac{\text{no of pixels in affected portion} * 100}{\text{total no of pixels in retinal portion}}$$







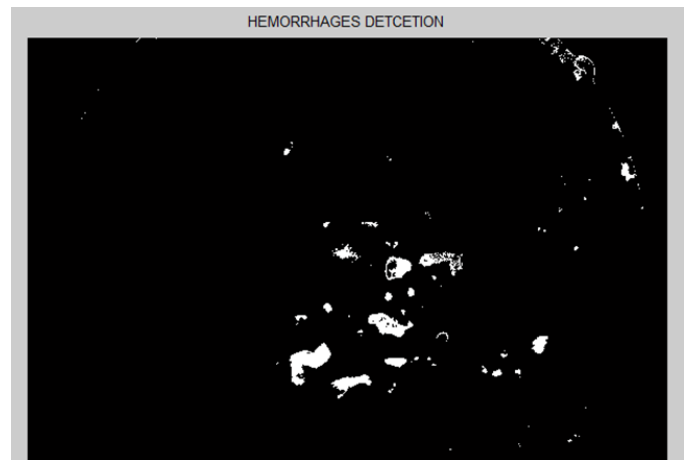
#### IV. MASKING SEGMENTATION

Masking involves locating some of the pixel values in an image to zero, or some other "background" value. Masking can be done in one of two ways: Use an image as a mask. A mask image is just an image where some of the pixel intensity values are zero, and others are non-zero. Anywhere the pixel intensity value is zero in the mask image, then the pixel intensity of the resulting masked image will be set to the background value (normally zero). Use a set of ROIs as the mask. The ROIs for each slice are used to label the mask. If you use ROIs as a mask, you might in addition perform soft masking, to set the intensity of masked pixels not to the background value, but a value that depends on how much of an individual pixel is within the mask. In general, pixels that are inside the mask do not have their pixel values changed: they are missing at the same intensity as the input image. Though, you can also generate images with binary intensity values (either 0 outside the mask, or 1 inside the mask) by selecting.

The Image Masking takes an input image, masks it, and produces a new image which is a copy of the input image, except that the new image will have its pixel intensity value

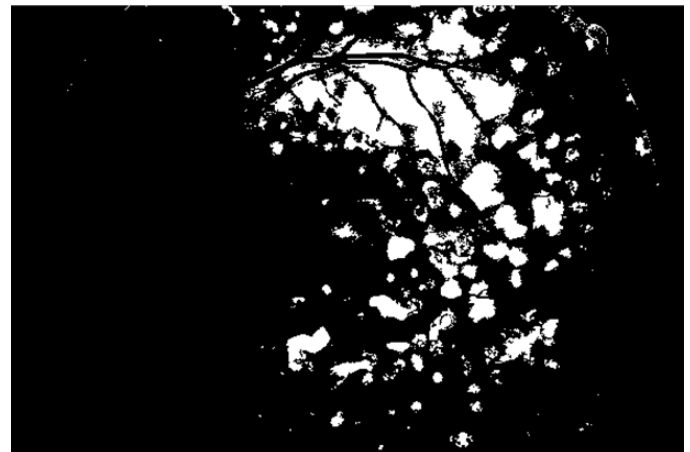
set to zero (or some other chosen background intensity value) in proportion to the mask and the masking operations performed.

Here we have performed masking based on the HSV image intensity values and abnormal regions will be represented as 1, normal regions will be represented as 0.



#### V. BINARY CONVERSION

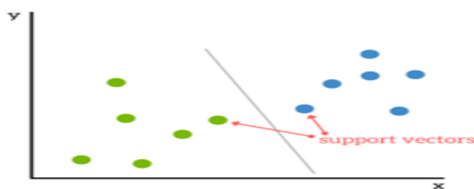
Binary images are produced from color images by segmentation. Segmentation is the process of assigning each pixel in the source image to two or more classes. If there are more than two classes then the usual result is several binary images. The simplest form of segmentation is probably Otsu's method which assigns pixels to foreground or background based on grayscale intensity. Another method is the watershed algorithm. Edge detection also often creates a binary image with some pixels assigned to edge pixels, and is also a first step in further segmentation.



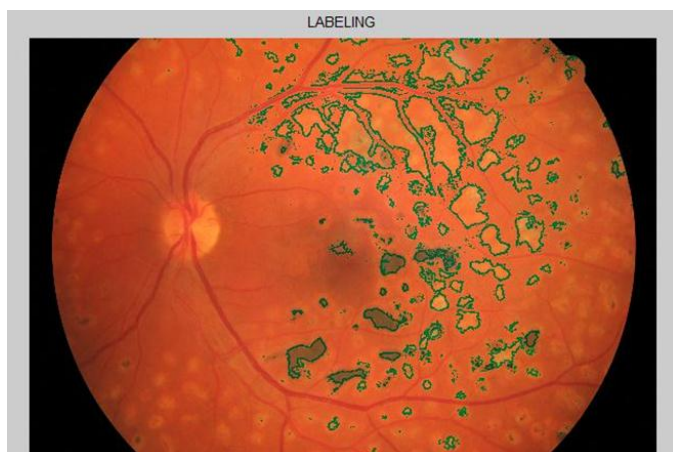
## VI. SVM CLASSIFICATION

Support Vector Machine (SVM) is a supervised learning technique that is used for discovering patterns for classification of data. An SVM model is a depiction of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. As well as performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

Classifying data is a common mission in machine learning. Assume some given data points each belong to one of two classes, and the objective is to choose which class a new data point will be in. In the case of support-vector machines, a data point is viewed as a  $p$ -dimensional vector, and we want to know whether we can separate such points with a  $(p-1)$ -dimensional hyper plane. This is called a linear classifier. There are many hyper planes that may classify the data. One reasonable preference as the best hyper plane is the one that represents the largest separation, or margin, between the two classes. So we prefer the hyper plane so that the distance from it to the nearest data point on each side is maximized. If such a hyper plane exists, it is called as the maximum-margin hyper plane and the linear classifier it is known as a maximum-margin classifier; or equivalently, the perception of optimal stability.



## VII. RESULT



## VIII. CONCLUSION

Diabetic retinopathy is a disease caused by increased permeability of retinal vessels. Its incidence and prevalence have been increasing due to urbanization, greater life expectancy and the habits of modern life. Its onset is insidious and it may lead to blindness in 75% of individuals who have been diabetic for more than 20 years. So we have developed image processing system to detect diabetic retinopathy at an early stage. Our proposed model can effectively segment out affected regions using masking algorithm and value plane exudates extraction. Finally we have calculated affected portion percentage using mathematical analysis. Our future work includes stages identification by extracting more features from fundus images.

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