

# PREVALENCE EVALUATION OF DIABETIC RETINOPATHY”

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**ABSTRACT:** Diabetic retinopathy is the cause for blindness in the human society. Early detection of it prevents blindness. Image processing techniques can reduce the work of ophthalmologists and the tools used automatically locate the exudates. Proliferative diabetic retinopathy is the most advanced stage of diabetic retinopathy, and is classified by the growth of new blood vessels. These blood vessels are abnormal and fragile, and are susceptible to leaking blood and fluid onto the retina, which can cause severe vision loss. First, vessel-like patterns are segmented by using Ridge Strength Measurement and Watershed lines. The second step is measuring the vessel pattern obtained [5][10].

Many features that are extracted from the blood vessels such as shape, position, orientation, brightness, contrast and line density have been used to quantitative patterns in retinal vasculature. Based on the features extracted, the segment is classified as normal or abnormal by using Support Vector Machine Classifier [6][8]. The obtained accuracy may be sufficient to reduce the workload of an ophthalmologist and to prioritize the patient grading queues.

**Keywords** - Diabetic Retinopathy, Microaneurysm , Vasculature , Watershed Transformation Disc., Optic

## I. INTRODUCTION

Diabetic Retinopathy (DR) is a severe and widely spread eye disease characterised by abnormal high blood sugar (hyperglycaemia) resulting from low levels of the hormone insulin. The progression of retinopathy is from mild nonproliferative abnormalities such as microaneurysm, to moderate and severe non-proliferative abnormalities such as exudates and haemorrhages, to proliferative diabetic retinopathy characterised by the abnormal vessel changes such as venous beading, intra-retinal microvascular abnormalities (IRMA) and growth of new blood vessels. Without timely treatment, the new blood vessels can bleed, leading to vitreous haemorrhage, fibrosis and retinal detachment. New blood vessels have a narrower calibre, more tortuous and are convoluted than normal vessels. New blood vessels are classified based on the position as new vessels on the optic disc and new vessels elsewhere. The development of the new vessels can be inhibited by early diagnosis and treatment.

Hence, screening of all diabetic patients (even without vision impairment) would help to diagnose the disease early enough for an optimal treatment. Although the prevalence of proliferative diabetic retinopathy is low, the onset of vision loss is considerably high. A number of studies have been made regarding the detection of microaneurysm , which is the first sign of diabetic retinopathy[9].

In this paper we proposed the method by combining the prior works of Optic Disc Segmentation and detection of new vessels to detect the disease Proliferative Diabetic Retinopathy. Since the optic disc is the entry point of most of the blood vessels, we focussed our attention towards the optic disc.

## II. SYSTEM DESIGN

### 2.1. Preprocessing

The green color plane was used in the analysis since it shows the highest contrast between the vessels and the retina. The green plane image is used for detecting the abnormalities in the vessels. The image was resized and the optic disc is located appropriately.

#### 2.1.1 Optic Disc Segmentation

The optic disc can be identified as a bright region on a retinal fundus image. In order to reduce computational time, the approximate locations of optic discs were identified, and regions of interest (ROIs) that included the optic discs were extracted from the images. The red color plane was used in the Optic Disc detection since it gives a better contrast of the OD region. A multidimensional image representation for the segmentation of the disc region. First, Gaussian filter is applied to the image at three different scales and summed. Second, a special case of texture filter bank is used[4][7].

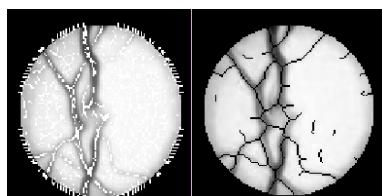
Next, Gabor filter is used at three different values and the result are summed Combining all the three steps a resultant image is obtained inwhich the circular hough transform is applied to initialize the contour. A region-based active contour model which useslocal image information at a support domain around each point of interest (POI) inspired by localized C-V models by using a richer form of local image information gathered over a multi-dimensional feature space is used for the segmentation of the optic disc.

## 2.2. Segmentation of blood vessels

Segmentation of the blood vessels are essential since the abnormal vessels are smaller, more tortuous and convoluted than the normal blood vessels. Several methods have been used for segmentation of the blood vessels. Ridges are defined as points where the image has an extreme in the direction of the largest surface curvature. The ridge strength can be calculated by the dark ridges that is formed by the vessel center lines.

The grey image forms the topographic surface. Watershed Transformation divides the image into regions based on the image grey level. The dividing lines are called the Watershed lines and the grouped regions are called the catchment basins. The grey image forms the topographic surface. Watershed Transformation divides the image into regions based on the image grey level. The dividing lines are called the Watershed lines and the grouped regions are called the catchment basins. The grey level is inverted such that the blood vessels form the watershed lines. The inverted grey image is filtered with the Gaussian filter such that over segmentation can be avoided. The watershed regions are calculated as follows,

1. A set of markers, pixels where the flooding shall start, are chosen.
2. The neighboring pixels of each marked area are inserted into a priority queue with a priority level corresponding to the grey level of the pixel.
3. The pixel with the highest priority level is extracted from the priority queue. If the neighbors of the extracted pixel that have already been labeled all have the same label, then the pixel is labeled with their label. All non-marked neighbors that are not yet in the priority queue are put into the priority queue.
4. Redo step 3 until the priority queue is empty. The Watershed Transformation produces closed regions connected by the watershed lines. The non vessel segments the mean value of along each candidate segment is calculated and candidates with mean values less than are discarded.



**Fig 2. Blood vessel Segmentation**

**(a) Ridgestrength Measurement.**

**(b) Watershed Transformation combines with Ridge strength.**

## 2.3. Feature Measurement

Fifteen features were calculated for each segment, based on characteristics human observers use to recognize abnormal vessels. The vessel origin was estimated as follows. First, a median filter was applied to remove smaller vessels. Next a threshold was applied to select the darkest 20% of pixels, which were assumed to belong to the major blood vessels. The centroid of the result was taken as the approximate origin of the major vessels. The following features were calculated for each segment[2][6].

- 1) **Segment length:** The length of each blood vessel from the origin calculated in pixel.
- 2) **Gradient:** The gradient magnitude of the image at each point gives the direction of the largest possible change in the intensity of the grey image. The gradient is calculated using Sobel gradient operator represents the convolution of original image with the kernel.
- 3) **Gradient Variation:** The standard deviation of the Sobel gradient is calculated. This feature is based on the observation

That the abnormal vessels have more contrast variation than the normal vessels.

- 4) **Direction:** The angle between tangents to the segment center point and a line from its center point to the vessel origin. The feature is based on the observation that normal vessels tend to radiate from the vessel origin towards the edge of the disc, whereas the direction of new vessels is more random.
- 5) **Tortuosity Measure 1:** The sum of the absolute changes in the tangential direction along segment path .
- 6) **Tortuosity Measure 2:** The difference in the angular extrema of the segment tangents.
- 7) **Tortuosity Measure 3:** The third tortuosity measure was the mean change in direction per pixel along the segment.
- 8) **Grey Level:** The normalized mean grey level are the maximum and minimum grey level values in the original image.
- 9) **Grey Level Coefficient of variation:** The ratio of the mean and standard deviation of the segment grey level values.
- 10) **Distance from origin:** The distance from the center of the segment to the vessel origin in pixel. This feature is based on the observation that the abnormal vessels occur towards the edge of the disc.
- 11) **Vessel Density:** The segment surrounding the vessel is determined .
- 12) **Number of Segments:** The total number of segments following the candidate segmentation. This feature is based on the idea that abnormal vessels have more number of segments than normal vessels.
- 13) **Mean Ridge Strength:**The mean strength of the ridge is calculated.
- 14) **Mean Vessel width:** The distance from each segment point to the closest edge point is assumed to be the vessel half-width at that point.
- 15) **Mean Vessel wall gradient:** The mean value of the Sobel gradient magnitude for all the vessel wall points.

### III. DETECTOR TRAINING AND TESTING

The Support Vector Machine (SVM) was chosen and used as the classifier for its rapid training and testing phase and for its good classification performance. Support Vector Machine is primarily a linear classifier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. In our paper, it represents two classes such as normal class and abnormal class.

The data for a two class learning problem consists of objects labelled with one of two labels corresponding to the two classes; the labels are +1 or -1. Since The system was trained with the normal and abnormal images.

As there were too few images with new vessels for separate training and test sets, the SVM was trained and tested simultaneously by leave-one-out cross validation.

The SVM was trained using all the images in the test set except the single test image, and this process was repeated for each image. The feature value normalization was also recalculated each time, leaving out the test image.

### CONCLUSION

We can significantly lower your risk of vision loss by maintaining strict control of your blood sugar level. Treatment does not cure diabetic retinopathy but it is effective in retarding vision loss and may, at least temporarily, improve vision. Most people with diabetes retain functional or near functional vision total blindness is very uncommon if retinopathy is treated. Efficacy of treatment if applied at optimal timing

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