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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 to detect Diabetic Retinopathy Patients. 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 seven 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, Proliferative Diabetic Retinopathy, Vasculature, Optic Disc, vessel segmentation.

I. INTRODUCTION

The effect of diabetes on the eye is called Diabetic Retinopathy (DR) which can lead to partial or even complete loss of vision if left undiagnosed at the initial stage. Diabetic Retinopathy is the leading cause of blindness in the working age population of developed countries. That is the reason for which efforts that has been undertaken in last few years in developing tools to assist diagnosis of diabetic retinopathy[2]. DR is caused by changes in the blood vessels of the retina. In some people with DR, blood vessels may swell and leak fluid or abnormal new blood vessels grow on the surface of the retina.

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 non proliferative 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[3]. 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[4]. In this system using seven features and as well as physical features we are recognizing diabetic retinopathy patients.

II. SYSTEMDESIGN

To evaluate the performance of this method,the digital retinal images were acquired using digital camera known as opthalmoscope.Fig(1) shows the input image. Fundus image is the interior surface of the eye,opposite the lens,and includes the retina,optic disc,macula,blood vessels and fovea[2].We tested and evaluated our proposed algorithm on several fundus images.The image set contains both normal and abnormal cases.

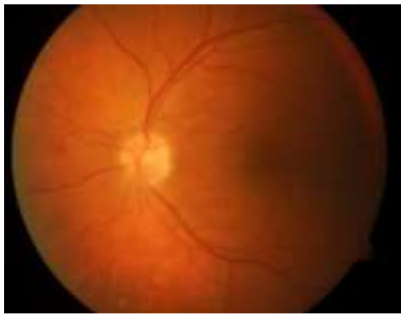

Fig1. Input image.

A. Preprocessing:

In this system images are preprocessed in to Red, Green and Blue plane to ensure adequate level of success in abnormality detection. RGB(Red, Green, Blue) images. The image taken from the fundus camera, eye image is converted into Red, Green and Blue plane as shown in Fig 2

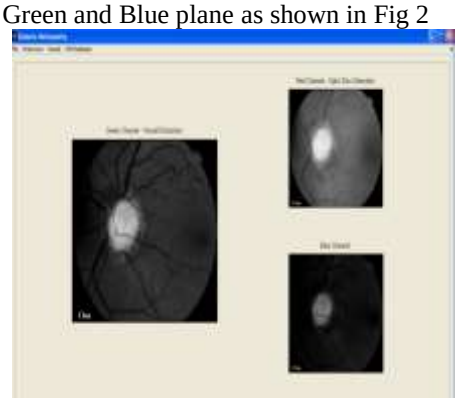

Fig.2 Red, Green and Blue Plane

The preprocessing stage is crucial to the algorithm success due to the intrinsic characterstics of retinal images. 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[4]. The image was resized and the optic disc is located appropriately. Filtering is used to suppress the unwanted noise as shown in Fig 3. which gets added into the fundus image. Here median filtering is used as it is very robust and has the capability to filter any outliers and is an excellent choice for removal of salt and pepper noise.

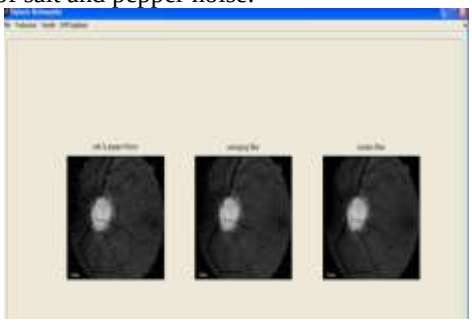

Fig.3.Filter RGB Plane

B. Optic Disc Segmentation:

The optic disc can be identified as shown in Fig.4 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[5]. This system gives good contrast of optic disc by adjusting image intensity values ,binarise the optic disc and removing small unwanted regions by filling up the holes optic disc is detected.

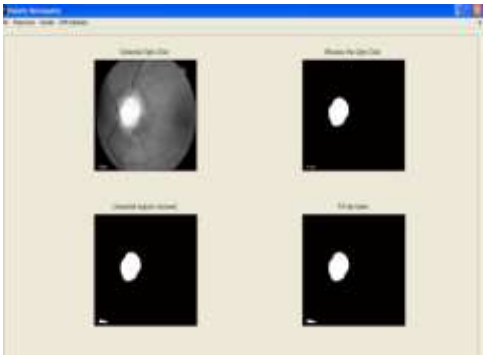

Fig4. Optic Disc detection

A multidimensional image representation for the segmentation of the disc region. Gabor filter is used at three different values and the result are summed Combining all the three steps a resultant image is obtained in which the circular hough transform is applied to initialize the contour[8]. A region-based active contour model which uses local image information at a support domain around each point of interest 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.As shown in Fig.5 extracted optic disc is determined by ROI.

Fig.5.Extracted optic disc

C. 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 had 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 extracted vessels are shown in fig.6 using dilate the edges. The grey image forms the topographic surface[9]. 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. Fig.7 shows the exact vessels on optic disc using soble gradient method.In this thin vessels and vessels branch points are filtered out.The non vessel segments the mean value of along each candidate segment is calculated and candidates with mean values less than are discarded.

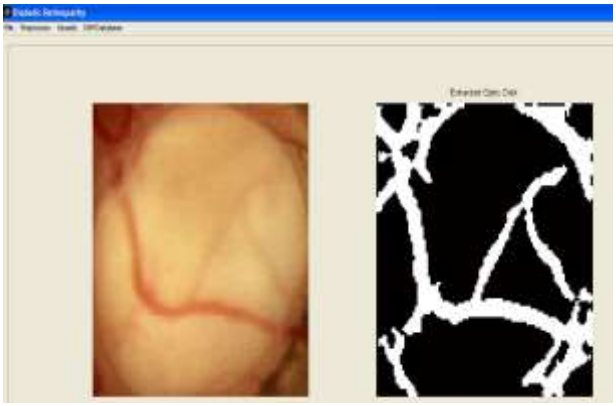

Fig.6 Extracted blood vessel

D. Feature Measurement

Seven features are calculated for each segment, based on characteristics human observers use to recognize abnormal vessels as shown in Fig.7. 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 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].

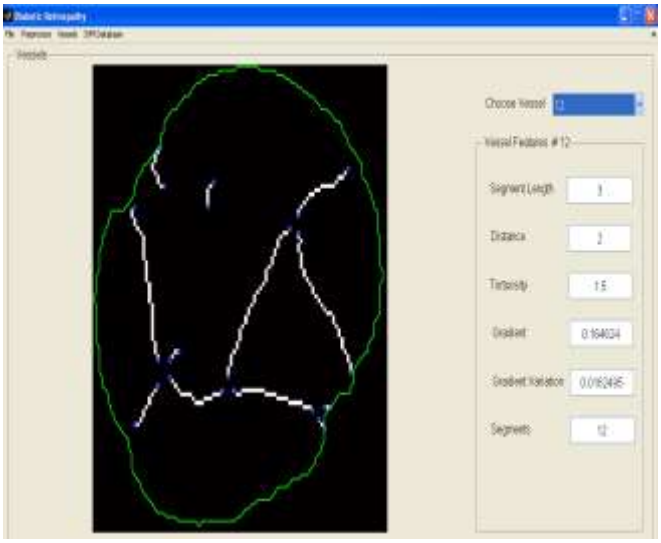

Fig7.vessels on optic disc with features

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 :** The sum of the absolute changes in the tangential direction along segment path The difference in the angular extrema of the segment tangents.The mean change in direction per pixel along the segment.
6) **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.
7) **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.

III. DETECTOR TRAINING AND TESTING

The Support Vector Machine (SVM) is 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 Diabetic Retinopathy class and normal 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 given seven fetures and physical features. 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.

IV. RESULT

The SVM is classifier, classification depends on the physical features and number of segments.Fig8,9,10,11 shows the results and condition and classifies as normal Patient and Diabetic Retinopathy Patient.

Fig.8

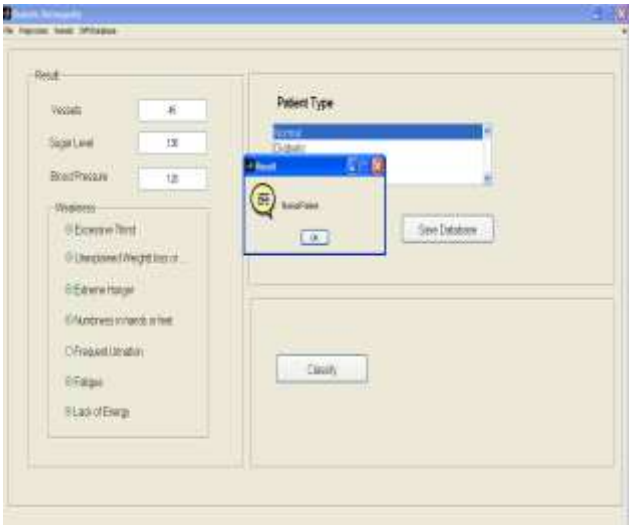

Fig 9

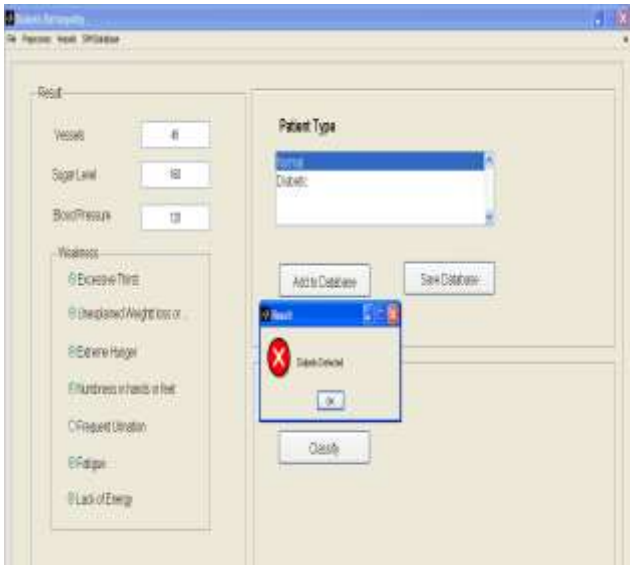

Fig.10

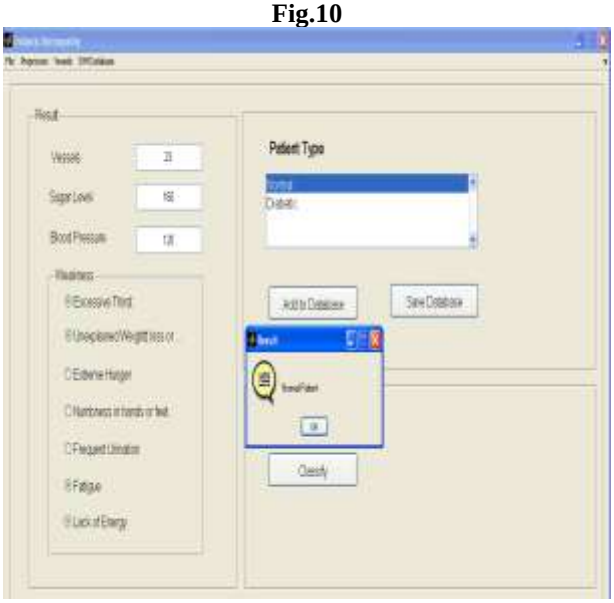

Fig.11

V. CONCLUSION

In this paper, we explore methods towards the development of an automated system for the purpose of detecting Diabetic Retinopathy. In this proposed system depending upon the seven features and human's physical features we are ease to find normal patient and Diabetic Retinopathy Patient. This system will help to find cause of blindness. We can significantly lower risk of vision loss by maintaining strict control of 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 not treated. Efficacy of treatment if applied at optimal timing.

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