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Identification of Diabetic Retinopathy in Fundus Images Using Segment Features and Morphological Features

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ABSTRACT: Diabetic retinopathy is a complication of diabetes and is a major cause of blindness in developed countries.. Proliferative diabetic retinopathy is characterized by development of abnormal disc vessels. The patients might not notice a loss of vision until it become too severe, hence early diagnosis and timely treatment is vital to delay or prevent visual impair and even blindness. This paper detects the presence of abnormalities in the retina by measuring segment features and wavelet based morphological features such as energy and entropy. This feature is input in to Support Vector Machine for automatic detection of new blood vessels to diagnose diabetic retinopathy. This approach achieves Sensitivity 93% and 95%Specificity.

KEYWORDS: Diabetic Retinopathy, Digital fundus images, segment features ,morphological features, Support Vector
Machine.

I. INTRODUCTION

Diabetic retinopathy, a complication of diabetes that occurs as a result of vascular changes in the retina, accounts for nearly five percent of the world's 37 million blind.Diabetic retinopathy (DR) is a common retinal complication associated with diabetes. It is a major cause of blindness in both middle and advanced age groups. Diabetes is the chronic state caused by an abnormal increase in the glucose level in the blood and which causes the damage to the blood vessels. The tiny blood vessels that nourish the retina are damaged by the increased glucose level.[3]

Diabetic retinopathy happens when the tiny blood vessels are damaged. These blood vessels are responsible for providing nutrients and oxygen to the retina. The person with diabetic retinopathy does not have a clear vision of the surroundings. Thus, he will face numerous problems and difficulties in his daily life routine. When his conditions become more severe, he will gradually lose his vision. Hence, early diagnosis or treatment will be able to prevent blindness complicated by diabetic retinopathy.

The various signs that appear are microaneurysms, dot and blot retinal haemorrhages, cotton wool spots, venous calibre changes and retinal capillary non-perfusion. Diabetes also causes retinal blood vessels to be more permeable resulting in transudation of serum components. This results in retinal thickening and causes macular oedema.[4]. Generally, diabetic retinopathy is classified into two main stages, namely nonproliferative diabetes retinopathy (NPDR) and proliferative diabetes retinopathy (PDR).

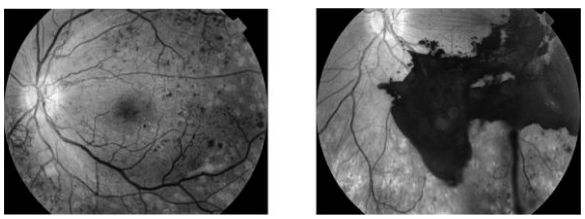

Fig. 1. Left: Proliferative retinopathy. Right: A slightly different view of the same eye at a later date showing a large, dark haemorrhage.

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Proliferative Diabetic Retinopathy is characterised by new vessels arising from retinal vasculature. When they are located at or within 1 disc diameter of the optic disc they are called neovascularization of the disc [NVD]. When they are further than one disc diameter from the optic disc they are called neovascularization elsewhere [NVE]. The stimulus for the development of these new vessels is thought to come from the ischaemic retina. Traction on these new vessels result in vitreous [gel inside the eye] haemorrhage. Fibro-vascular proliferation can also result in tractional retinal detachment. Traction on the retina can also cause retinal breaks resulting in rhegmatogenous retinal detachment.[4]

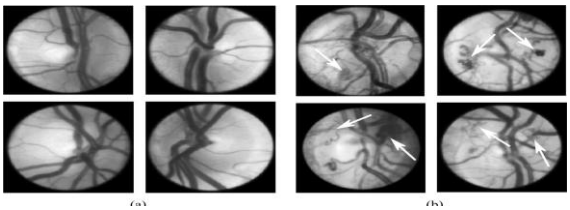

Fig. 2 (a) Examples of (a) normal discs and (b) discs containing abnormal vessels. The white arrows indicate some of the abnormal vessels.

II. LITERATURE SURVEY

During the recent years, there have been many studies on automatic diagnosis of diabetic retinopathy using several features and techniques .(Banumathi et al, 2003) have analyzed the performance of three different template matching algorithms in respect of the detection of blood vessels in the retinal images for both gray level and color images. Blood vessels detection using the proposed 2D Gaussian matched filtering gives the complete and continuous vessel map of the blood vessels .

There have been an increase in the use of digital image processing techniques for the screening of DR after it was recommended as one of the method for screening DR at the conference on DR held in Liverpool UK in 2005 [5]. Most of the available work done can generally be categorized into screening of Background Diabetic Retinopathy (BDR) and Proliferative Diabetic Retinopathy (PDR) while diagnosis of Severe Diabetic Retinopathy (SDR) has been left for the ophthalmologist.

Retinal images are acquired by a specialized camera called fundus camera. Mydriatic and non-mydriatic [9] fundus cameras are used for retinal photography.Pre-processing is an essential step in retinal image analysis which attenuates image variation by normalizing the original image with a reference model. It helps in reducing the intra image as well as inter image variability.Blood vessels segmentation helps in diagnosis and treatment of ophthalmologic conditions. Gray level variations in the cross section of the retinal vessels is Gaussian shaped .So, matched filter is used for segmentation of blood vessels. Hatanaka *etal.*, extracts the blood vessels by using density analysis. [7]

The objective of the feature extraction is twofold: (a) Generating a feature set which maximizes the within-class similarity and minimizes the between-class similarity measures & (b) Aid in dimensionality reduction which ultimately
minimizes the convergence time period of the classifiers.
Morphological operations are also used in this work to enhance the quality of the results. Lack of systematic evaluation of the results is the major drawback of this technique.Radim et al (2002) have used the nonlinear filtering technique to extract the optical disk.This approach is less susceptible to noise and filtering is followed by edge detection to extract the region of interest. But this method is not applicable for low contrast images. Snake active contour methodology for optical disk detection is proposed by Thitiporn et al (2003). The contrast of the optical disk is used as the significant feature in this work. But the initialization of size and shape of the contour is the practical difficulty of this approach. Active shape model (ASM) based optical disk detection is implemented by Huiqi et al (2003) [9]In recent years, SVM classifiers have demonstrated excellent performance in a variety of pattern recognition problems [16, 24, 25]. SVMs were initially designed for the two-class problems but subsequently extended to multi-class problems.[3]

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III. METHOD

DATA

Due to the low prevalence of new vessels in the screening population, images were collected from a hospital. A fundus camera provides an upright, magnified view of the fundus.

A typical camera views 30 to 50 degrees of retinal area, with a magnification of 2.5x, and allows some modification. of this relationship through zoom or auxiliary lenses from 15 degrees which provides 5x magnification to 140 degrees with a wide angle lens which minifies the image by half.80 images are collected to analyse the system.

IV. PROPOSED METHOD

A .Flow Chart

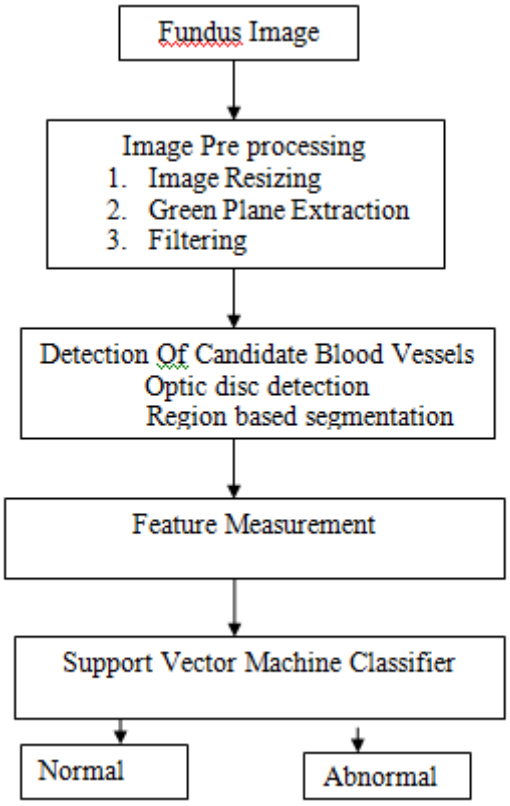

Fig 3 Work Flow Diagram

A. Image Pre-Processing

Blood vessels are extracted in this paper for the identification of diabetic retinopathy. The contrast of the fundus image tends to be bright in the centre and diminish at the side, hence preprocessing is essential to minimize this effect and have a more uniform image. The green color plane is used in the analysis since it shows the best contrast between the blood vessels and retina.

As most image samples are not consistent in sizes, images are all resize to a 800 by 800, maintaining uniformity in our image data for image analysis. Next, the colour space of the image is adjusted to gray image, extracting only the Intensity component of the original image.Once the image is processed, it is again being process by anisotropic filtering to remove any unwanted impulse noise. Image pre-processing is a process to reduce the presence of unwanted features of the image such as noise.

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B. Extraction of Candidate Blood Vessels

Compared with normal vascular abnormal disc vessels are smaller and more tortuous.Detection is aided by the bright background which gives greater vessel contrast on disc.The ridges formed by the vessel center lines may be detected through ridge strength.

The detection of the optic disk in fundus images is a very important task because of its similarity in brightness, color and contrast to the exudates. It invariably appears in exudates detection results and hence there is a need to mask it out.Moreover, the optic disk is an important retinal feature and can be used for registration of retinal images.

The green channel of the image is applied with morphological image processing to remove the optical disk. Image segmentation is then performed to adjust the contrast intensity and small pixels considered to be noise are removed.Another green channel image is processed with image segmentation and combined with the mask layer. These two images are compared and the differences are removed. The obtained image would represent the blood vessels of the original

Image segmentation is used to locate the objects or boundaries in the image. In edge detection function, the contours of the objects are extracted from the image.Canny method is used for this project as it is better compared to the other similar Matlab functions by having two different thresholds to detect the edges [7]. Image segmentation is also the process of selecting of pixels that are similar in certain characteristics such as intensity.

C.Calculation of feature values

Segment features are nalyse theproposed ,based on partly on observation of the characterstic is use to recognize abnormal vessels. Several feature measures require the angle oftanget at each point in the segment.First a median filter was applied to remove smaller blood vessels.[1]The following features were calculated for each segment.

1. Segment length
2. Gradient
3. Gradient variation
4. Grey Level
5. Grey Level Coiefficent Of variation
6. Mean ridge strength

1)Segment length: The length of the segment in pixels.

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2) Gradient: The mean gradient magnitude along the segment using the Sobel gradient operator. The mean gradient magnitude along the segment using the Sobel gradient operator. The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges.

3) Gradient variation: The standard deviation of the Sobel gradient along the segment. This feature is based on the observation that abnormal vessels are less well defined, being less homogeneous with more contrast variation than normal vessels.

4)Grey Level:

The normalized mean segment grey level where is the grey level of the the segment pixel and are calculated maximum and minimum grey level values in the original image, respectively.

$$g_{norm} = \frac{1}{G_{\max} - G_{min}}[(\frac{1}{n \sum_{i=1}^{n} g_i}) - G_{min}] \quad (1)$$

Greylevel denotes monochromatic intensity .

5)Grey Level coefficient of variation:

This measure was based on the observation that new vessels appear less homogeneous than normal vessels. It is calculated as the ratio of the mean and standard deviation of the segment grey level values.

6)Mean Ridge Strength:

The dark ridges formed by the vessel center lines may be detected using the ridge strength (contour curvature given where is the Gaussian filtered image (the standard deviation of the Gaussian function determines the scale of the

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ridges detected). The subscripts indicate partial derivatives, for example is the first partial derivative of with respect to and is the second partial derivative with respect to . is positive for ridges such as the vessel center lines, and negative in the valleys between vessels. is undefined in regions where the gradient is zero in both the and directions.

$$K = \frac{L_{x^2} L_{yy} + L_{y^2} L_{xx} - 2L_x L_y L_{xy}}{(L_{x^2} + L_{y^2})^{3/2}} \quad (2)$$

where ridge strength (contour curvature), given by is the Gaussian filtered image (the standard deviation of the Gaussian function determines the scale of the ridges detected).
[1]

B. Determination of Morphological Features

Automated classification into retinas with or without PDR requires high accuracy to be able to support screening programs currently carried out by ophthalmologists. With the exception of the area, perimeter, and circularity, all are based on data obtained from the application of the derivatives-of- Gaussian wavelets to the automated segmented vessel skeletons.

D Wavelet Transform for Morphological Analysis

Different differential morphological features were obtained,inspired by the shape analysis approach used for characterization of retinal ganglion cells. In this paper,we utilized the order to compose a wavelet gradient. The morphological features described below first derivative of the Gaussian function in are calculated based on the derivatives-of-Gaussian wavelet.

1. Curvature
The skeleton outline curvature represents how the direction of a unit tangent vector varies along the shape contour.

$$k = \nabla . \frac{\nabla f}{||\nabla f||} \frac{f_x \quad f_y{}^2 - 2 f_x f_y f_{xy} + f_{yy} f_x{}^2}{(f_x{}^2 + f_y{}^2)^{3/2}} \quad (3)$$

where fx, fy, fxx, fyy, and fxy denote the first partial derivatives of f with respect to x and y, the second partial derivatives of f with respect to x and y, and the partial derivative with respect to x and y, respectively. These partial derivatives are estimated using the 2D wavelet transform in the same spirit described above for the gradients.

2. Orientation Entropy
The orientation entropy E indicates the orientation disorder degree encountered in a shape and is obtained from the angular distribution of the vector field .

$$E = -\sum_{i \in K} P_i \ln(p_i) \quad (4)$$

where pi is the occurrence frequency of some vector oriented toward the i direction and K is the set of bins in the histogram.

3. Continuous Wavelet Transform Second
Moment
The second moment of the CWT modulus is a statistical dispersion measure to indicate biases in the gradient vector field. If q is the CWT modulus histogram, with each bin qi centered at i, then its CWT second moment is

$$m = \sum_{i \in K} i^2 q_i \quad (5)$$

4. Correlation Dimension
According to chaos theory, the correlation dimension (CD) measures the dimension of the space occupied by a set of random points, or in other words, it gives the probability of finding two points closer than a certain distance.[14]

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$C(\varepsilon) = \lim_{n\to N^2} \frac{2}{N^2} \sum_{i=1j>i}^{N} \theta(\varepsilon - |X_i - X_j|)$

Where the Heaviside function is defined as $\theta(\varepsilon - |X_i - X_j|)$

$$\begin{cases} if(\epsilon - |X_i - X_j| \geq 0 \\ if(\varepsilon - |X_i - X_j \leq 0 \end{cases} \quad (6)$$

and the CD itself is taken as the slope of the logarithm of the correlation integral.

E Classification

Support vector machine is used as the classifier for good classification performance. A support vector machine (SVM) is a concept in computer science for a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The kernel function used is

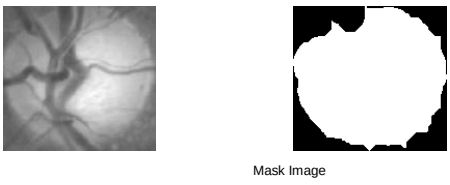
$k(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2$ (7)

All the features are normalized before classification

Although users do not need to understand the underlying theory behind SVM, we briefly introduce the basics necessary for explaining our procedure. A classication task usually involves separating data into training and testing sets. Each instance in the training set contains one \target value" (i.e. the class labels) and several \attributes" (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

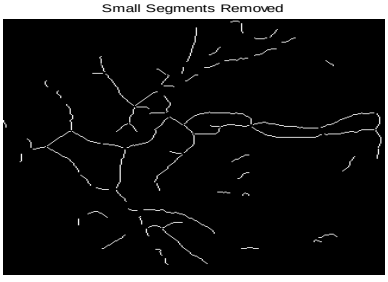
A Support Vector Machine is chosen as classifier for its good classification performance.The orginal SVM algorithm is a linear classifier which finds the best hyperplane separating two classes.All the features were normalized before classification. SVMs belong to a family of generalized linear classifiers and can be interpreted as an extension of the perceptron.The SVM estimates a probability of abnormality for each vessel segment .For the detection of abnormal images the single segment with the highest abnormality probability was selected and compared with a threshold .

V. EXPERIMENTAL RESULTS



(a) (b)

Fig2 a)Input image after pre processing
b)Mask of input image



.Fig3 Blood Vessels Extracted

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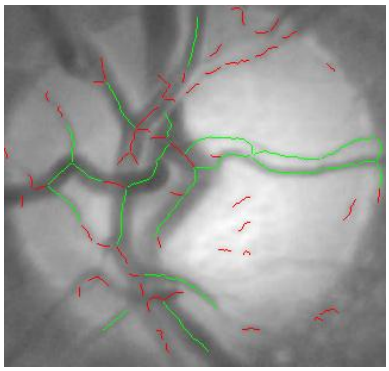

Fig 4 candidates classified as abnormal.

Blood Vessel	Gradient variation	Segment Length	Gradient variation	Grey Level Coiefficent Of variation
Abnormal	2.1252	9	1.5754	380.8949
Normal	1.7057	11	0.9259	111.15

Since we are interested primarily in automated detection of PDR, we proceed to further analyze the automated data only. These data were normalized so that each feature has zero mean and standard deviation of one.

Several of these candidate segments are correctly classified as abnormal in (d). The MATLAB code took 35 s on an Intel 5160 Xeon processor (3 GHz) to calculate the fifteen features for each image.Classification took less than one second per image. The classifier training phase took 2 min, but this only has to be performed once prior to using the system.

VI. DISCUSSION

In a typical U.K. screening programme approximately two thirds of patients have no visible signs of retinopathy [6] and are simply recalled for screening after twelve months.

There are so many classifiers namely, feed forward neural network, fuzzy classifier, Gaussian mixture model, Support Vector Machine (SVM) and Probabilistic neural network etc. In this work, Support Vector Machine was used for classifier.In recent years, Support Vector Machine (SVM) classifiers have demonstrated excellent performance in a variety of pattern recognition problems .

This paper has demonstrated an automated system which is able to distinguish normal and abnormal vasculature on the optic disc. It could form part of a system to reduce manual grading workload or a tool to prioritize patient grading queues.

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