Diabetic Retinopathy Evaluation using the support vector machine

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Abstract - *Diabetic retinopathy is a micro vascular complication which is characterized by several changes in the retina. These changes need to be detected early so that steps for further handling and treatment can be determined. Laser therapy is one of the common therapies for patients with Diabetic Retinopathy. This therapy is a manual examination of the scanned results of the fundus retinal image. Manual examinations that generate ophthalmologist sight differ from each other. To overcome this problem, a special program is needed to analyze the fundus image of the eye. To create a special program for analyzing the fundus images of the eye required several stages of research. The study begins by preprocessing eye fundus images, getting rid of the optic dick form the fundus of the eye and then separating the vascular tissue of the damaged area of the retina. Damaged areas of the retina consist of dark and bright lesions. Mathematical morphology methods are used to detect the presence of dark lesion. As diabetes progresses, the vision of a patient may start to deteriorate and lead to diabetic retinopathy. The main stages of diabetic retinopathy are no proliferative diabetic retinopathy(NPDR) and pro-liferative retinopathy(PDR). In this paper, we have proposed a computer based approach for the detection of diabetic retinopathy stages using color fundus images. The features are extracted from the raw image, using the image processing techniques and fed to the support vector machine (SVM) for classification. The results showed a sensitivity of 99.45% for the classifier and specificity of 100%.*

Key Words: **SVM, NPDR, Classification, Segmentation**

1. INTRODUCTION

Diabetic retinopathy is damage to the retina (retinopathy), specifically blood vessels in the retina, caused by complications of diabetes mellitus. Diabetic retinopathy can eventually lead to blindness if left untreated. Approximately 80% of all patients who have had diabetes for at least ten years suffer from some degree of diabetic retinopathy. The retina is the light sensitive membrane that covers the back of the eye. If diagnosed and treated early blindness is usually preventable. Diabetic retinopathy generally starts without any noticeable change in vision. However an eye doctor can detect the signs. Blood vessel extraction from the fundus images poses an important step to solve various practical applications, diagnosis of the retinal vessels and registration of retinal images acquired at different times. Blood vessel detection plays an important role in automated radiological diagnosis tic process. There are several existing segmentation methods but all of them failed to extract. In this project edge enchancement technique and object classification is focusing to remove the objects from the fundus image. Retinal vasculature has received attention by specialists in different pathologies, where the detection and analysis of retinal vasculature may lead to early diagnosis and prevention of several diseases, such as hypertension, diabetes, arteriosclerosis, cardiovascular disease and stroke. One of the well-known and commonest diseases that need a computer- aided medical diagnosis is diabetic retinopathy (DR), which leads in most cases to partial or even complete loss of visual capability. The accurate diagnosis of this disease depends upon some features which have to be analysed in order to quantify the severity level of the disease. Retinal blood vessels are considered as one of the most important features for the detection of DR. As diabetic retinopathy is a progressive disease, regular screening of the human retina is essential for reducing the proliferative diabetic retinopathy and for preventing the subsequent loss of visual capability. The edge enhancement technique and object classification is mainly focused in this paper to remove the small objects from the fundus image. The remaining part of this paper is organized as follows. The blood vessel extraction technique based on the mathematical morphology is described in proposed methodology section.

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 2-D Gaussian matched filtering gives the complete and continuous vessel map of the blood vessels . (Bevilacqua et al, 2005) proposed a computational model to extract, from eye fundus images, the retinal vasculature and then to detect its features such as bifurcations and crossover points of retinal vessels. (Edgardo Felipe-Riveron et al, 1989) have proposed to extract the vascular network, using morphology operators . (Herbert F. Jelinek et al , 2007) have proposed that fluorescein-labeled retinal blood vessels of 27 digital images were automatically segmented using the Gabor wavelet transform and classified using traditional features such as area, perimeter and an additional five morphological features based on the derivatives-of-Gaussian wavelet-derived data. (Mohammed Al-Rawi et al , 2006) proposed that , the matched filter response to the detection of blood vessels is increased by proposing better filter parameters . (D. Vallabha et al , 2004) proposed a method to distinguish mild NPDR from severe NPDR using a procedure that involves Global image feature extraction. The vascular abnormalities are detected using scale and orientation selective Gabor filter banks .

(Wong Li Yun et al, 2008) have used back propagation algorithm for classification of the four stages of eye images of Diabetic Retinopathy. The features are extracted from the raw images using the image processing techniques and fed to the feed forward neural network classifier for classification.

2. METHODOLOGY

A Diabetic retinopathy is a potentially blinding complication of diabetes. Early stage of vision loss diagnosis is one of the challenge processes. The main objective of this project is to improve the quality of colour fundus image vessel segmentation and to identify the diabetic retinopathy by using SVM algorithm and evaluating the performances of this segmentation. To improve the classifier accuracy depends upon the retinal blood vessel features.

A number of experiments were performed to compare the performance of each of the methods on the DRIVE database. The procedure applied in this study was aimed at comparing the matching degree of certain QEFs with human perception and can be summarized as follows. Different vessel segmentations [3] of the first five eye-fundus images from the DRIVE database test set were selected. Then, 20 human observers were asked to score quality between the segmentations and the reference standards. In this process, the original color retinal images were also shown to the observers. Thus, they could overlay the segmentations on the color image and check segmentation goodness of fit. Scores were real numbers within the [0,10] interval, where 0 and 10 denote the worst and best quality cases, respectively. A subjective human perception of quality can be then obtained. In addition to this, the values of the QEFs [7] under study were also calculated for the same images. Thus, human- and functions-provided evaluations are compared to measure the correspondence degree between them through some statistical approach.

Preprocesing is the process we resize the image as per the requirements. Also we enhance the brightness of the image. The importance of image resizing scheme is greatly felt in the fields of medical image processing, computer graphics, image database etc. Image resizing is an operation that enlarges or reduces the size of the displayed image. The two main purposes of resizing images are to increase the size of the object within the image for ease of visualisation and to decrease the size of the image so that the entire image can be visualised on a monitor or display device with a lower spatial resolution than the image itself.

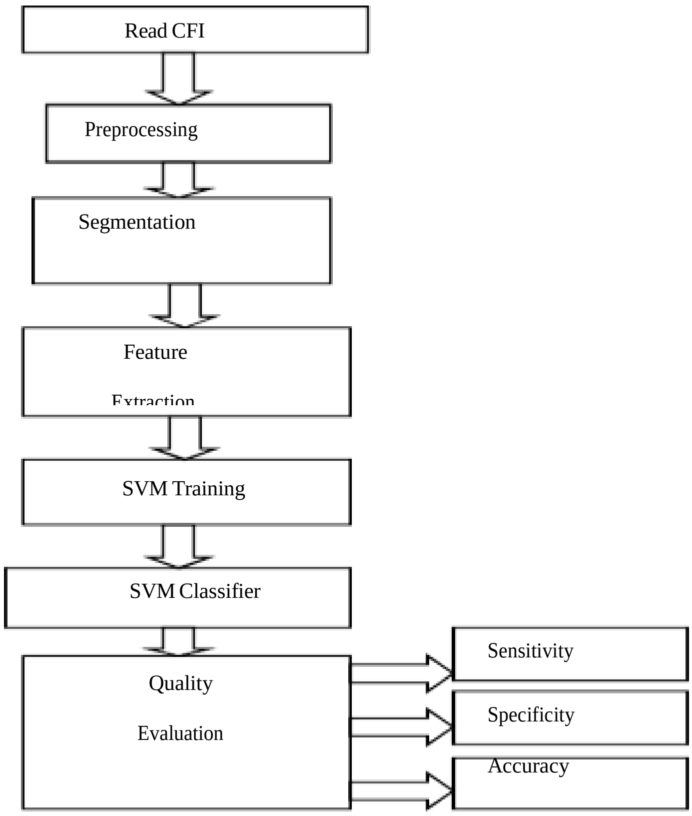

Fig 1: Block Diagram

During the process of resizing, image pixels are mapped onto a smaller or larger image matrix. Various methods to achieve the remapping of pixels are used. The common methods are nearest neighbour interpolation and bi- linear interpolation. Another more time-consuming method is bi-cubic or cubic convolution.

The enhancement is widely used for medical image processing and as a preprocessing step in speech recognition, texture synthesis, and many other image/video processing applications. The final preprocessing step consists on generating a new vessel enhanced image, which proves more suitable for further extraction of moment invariants based features while bright retinal structures are removed (i.e., optic disc, possible presence of exudates or reflection artifacts), the darker structures remaining after the opening operation become enhanced (i.e., blood vessels, fovea, possible presence of microaneurysms or haemorrhages).

2.1 SEGMENTATION

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. Wavelet transform decomposes a signal into a set of basis functions.

These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet $\psi(t)$ called mother wavelet by dilations and shifting, The mother wavelet used to generate all the basis functions are designed based on some desired characteristics associated with that function. DWT2 is a Single-level discrete 2-D wavelet transform [35]. The dwt2 command performs a single - level two-dimensional wavelet decomposition with respect to either a particular wavelet or particular wavelet decomposition filters. [cA,cH,cV,cD] = dwt2 (X,'wname') computes the approximation coefficient matrix cA and details coefficients matrices cH, cV, and cD for horizontal, vertical, and diagonal, respectively, obtained by wavelet decomposition of the input matrix X where X is the given input eye image after applying adaptive histogram equalization. The 'wname' string contains the wavelet name. Haar wavelet is used. As a result of applying this DWT to the eye images, the size of the images is reduced to half without any change in the information content of an image. So the size of the eye images is now 640 × 512. The resulting images are shown in Fig.5.

2.2 FEATUREEXTRACTION [HAEMORAGHES]

Both Hemorrhages and Exudates appear as bright lesions in retinopathies images and have sharp edges and high contrast with the back- ground. We perform boundary detection for exudates using thresholding and morphological processing algorithms. Fig. 8 gives the Block diagram for Haemorrhages or Exudates Detection. The following steps are applied to detect the Haemorrhages or Exudates.

2.2.1 GREEN COMPONENT

The retinal image is taken in the RGB form by fundus camera. The green channel of the RGB space is extracted and chosen for detection of exudates because exudates appear most contrasted in this channel. So the first step is to separate this channel to a new image

2.2.2 THRESHOLDING

Thresholding is a simple shape extraction technique, where the images could be viewed as the result of trying to separate the eye from the background. Thresholding is a method of producing regions of uniformity within an image based on some threshold criterion, T. The T can be defined as,

$$T = T\{x, y, A(x, y), f(x, y)\} \quad (9)$$

where, $f(x, y)$ is the gray level of the pixel at (x, y) and $A(x, y)$ denotes some local property in the neighborhood of this pixel.

A thresholded image,

$$g(x,y) = 1 \text{ if } f(x,y) \geq T$$

$$g(x,y) = 0 \text{ if } f(x,y) < T$$

A Local Thersholding technique is one that partitions the given image into sub-images and determines the threshold for each of these sub-images.

$$T = T\{A(x, y), f(x, y)\}$$

where, T is dependent upon a neighbourhood property of the pixel well as its grey-level value. The main task of thresholding is to highlight high values of wavelet coefficients which almost correspond to the optic disc and suppress small values which correspond to noise or unimportant structures in the image. To the morphologically eroded image, local thresholding is applied.

2.2.3 MORPHOLOGICAL PROCESSING

Erosion involves the removal (alteration) of pixels at the edges of regions, for example changing binary 1 value to 0, while dilation is the reverse process with regions growing out from their boundaries. These two processes are often carried out using a form of kernel known as a structural element.

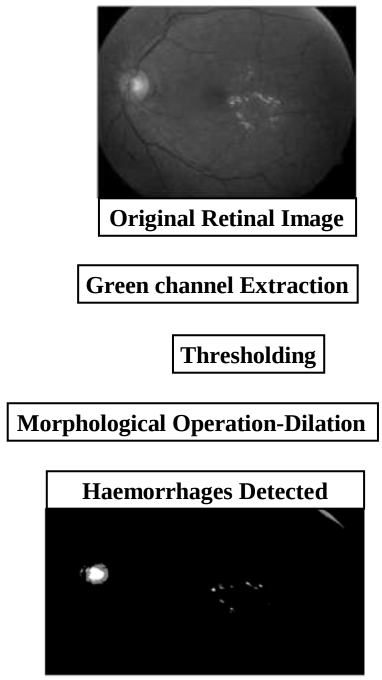

Fig.2. Block diagram for Haemorrhages Detection

A structural element is an $N \times N$ kernel with entries classified according to a binary scheme, typically as 0 or 1. If all entries are coded 1 then the structural element is a solid square block, the center of which is laid over each pixel in the source image in turn.

The shape of the structural element may vary, for example as a vertical bar, horizontal bar, cross shape or a user-defined pattern. If dilation is followed by erosion the process is described as a Closing operation, whilst Erosion followed by dilation is known as Opening. These processes are not symmetric, and thus are generally not reversible. Opening eliminates small and thinner features, resulting in smoother edged regions, while closing also smoothes shapes but makes thin narrow features larger and eliminates small holes and narrow gaps. Here Dilation is used after thresholding and the exudates or Haemorrhages are detected. Fig.9 gives the NPDR and PDR affected images and their corresponding Haemmorrages and Exudates detected images.

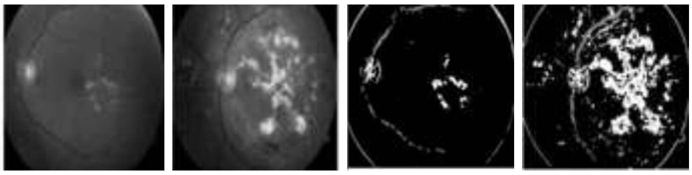

Fig.3. (a). NPDR Image (b). PDR Image (c). aemorrhages Detected Image (d). Exudates Detected Image

After performing the above mentioned preprocessing steps, the new eye image that is blood vessel detected image and Haemorrhages or exudates detected images are obtained. A set of feature values is taken from both blood vessel and Haemorrhages or exudates detected images. The feature values that are extracted are: Radius, Diameter, Area, Arc length, Center Angle and Half Area. Table.1 gives the range of feature values obtained for DR Diagnosis in our work.

Table 1: feature extracted values

Features / **Types of Eye Images**	**Radius (cm)**	**Dia (cm)**	**Area (cm^2)**	**Arc length (cm)**	**Centre angle ([illegible])**
Normal	144-156	260 - 320	65 - 80	5.7 - 7.6	2.2 - 2.6
NPDR	311 - 346	625 - 643	304 - 324	60.9 - 63.6	10.6 - 11.3
PDR	421 - 426	843 - 854	558 - 572	143 - 148	19.4 - 19.8

2.3 SVM modeling technique for classification

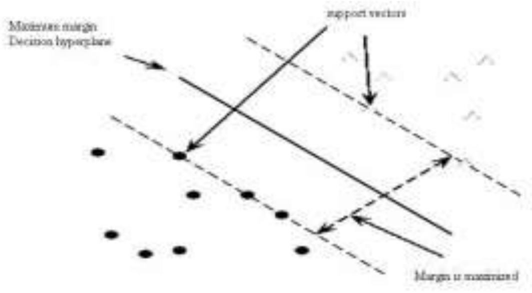

Figure 4: Optimal Hyperplane , mximizing margin and support vectors

After the feature extraction methods, the extracted features of images are given as inputs to Svm . Svm is used to classify the group of eye images as either affected or normal depending on the feature values. Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. It is described in detail by (Vapnik , 1998) , an SVM model is a representation 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. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on . As shown in Figure : 10 , a support vector machine, constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class , since in general the larger the margin the lower the generalization error of the classifier. A Support Vector Machine (SVM) performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. The input space is mapped into a high dimensional feature space . Then, the hyperplane that maximizes the margin of separation between classes is constructed. The points that lie closest to the decision surface are called support Vectors and directly affect its location. When the classes are non-separable, the optimal hyperplane is the one that minimizes the probability of classification error. So the goal of SVM modeling is to find the optimal hyperplane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other side of the plane. The vectors near the hyperplane are the *support vectors*. In simple words, given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other.To fit nonlinear curves to the data, SVM make use of a *kernel function* to map the data into a different space where a hyperplane can be used to do the separation. In this work, we have used polynomial kernel which is given by,

3. Results and discussion

A screened fundus is considered as a true positive (TP) if the fundus is really abnormal and if the screening procedure also classified it as abnormal. Similarly, a true negative (TN) means that the fundus is really normal and the procedure also classified it as normal. A false positive (FP) means that the fundus is really normal, but the procedure classified it as abnormal. A false negative (FN) means that the procedure classified the screened fundus as normal, but it really is abnormal. Sensitivity is the percentage of abnormal funduses classified as abnormal by the procedure. *Sensitivity =TP/TP + FN.* Specificity is the percentage of normal funduses classified as normal by the procedure. *Specificity =TN/TN + FP* The higher the sensitivity and specificity values, the better the procedure .

The Quality Evaluation Function (QEF) is compared from this perspective to commonly-used metrics (Se, Sp, and Acc) and other general QEFs that, to the best of our knowledge, have not been extensively used in retinal vessel segmentation [7]. The aim is the subjective evaluation of the behavior of these functions in terms of correspondence with human perception.

Sensitivity (Se): Sensitivity (Se) metrics are the ratio of well-classified vessel and non-vessel (background) pixels.

Specificity (Sp): Specificity (Sp) metrics are the ratio of well-classified vessel and non-vessel (background) pixels, respectively.

Accuracy (Acc): Accuracy (Acc) is a measure that provides the ratio of total (both vessel and nonvessel) well-classified pixels.

Table 2: performance index in terms of %

Sensitivity	Specificity	
99.45	100.00	98.92

The features such as blood vessels area, mean and standard deviation corresponding to three classes are extracted using the proposed algorithms. The results of the SVM classification are shown in Table 1. Table 2 shows the result of Sensitivity, Specificity and Percentage of accuracy , for the three classes of eye images using Support vector machine classifier. Our results show that the classifier is able to identify all the normal class. In the case, of NPDR and PDR, our classifier is able to identify their class up to 97.84% and 98.93% respectively. The sensitivity of the system is 99.45% and specificity is 100.00%. The percentage of accuracy of the proposed system is 98.92%.

Table 1: Results of SVM classification

Classes	ned	of Tested Images	Correctly Classified Images	%classification
Normal	50	30	30	100.00
NPDR	100	93	91	97.84
PDR	100	94	93	98.93

4. Conclusion and future work

This work determines the presence of Pro-liferative diabetic retinopathy and Non- proliferative diabetic retinopathy or otherwise in a patient by applying techniques of digital image processing on fundus images taken by the use of medical image camera by a medical personnel in the hospital. In this work, we have investigated and proposed a computer-based system to identify normal , Non-proliferative diabetic retinopathy and Pro-liferative retinopathy. The Proposed system demonstrated a classification sensitivity of 99.45% and specificity of 100.00%. This work indicates that support vector machines can be effectively used for image classification. Eventhough by now some progress has been achieved, there are still remaining challenges and directions for further research, such as , extracting different features and developing better classification algorithms and integration of classifiers to give better performance and reduce the classification errors.

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