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Identification of Diabetic Retinopathy from Segmented Retinal Fundus Images by using Support Vector Machine

P.R. Thorat, K.V. Patil

Abstract: ***Segmentation of images has become important and effective tool for many technological applications like vessel segmentation from fundus images, medical imaging and many other post-processing techniques. Diabetic Retinopathy is an eye disease which is caused by changes in blood vessels of retina of diabetes. It is the primary cause of blindness in the universe. To avoid blindness of diabetes detection of diabetic retinopathy as early as possible is the only option as number of persons are becoming blind because of this disease. Many studies have shown that early diagnosis is the most efficient way to cure this disease. This paper presents identification of diabetic retinopathy from segmented retinal images by using support vector machine. In pre-processing, first the input image is converted into green channel image and converted into binary image. After that we have segmented the vessels using thresholding. For tracing of vessels, graph tracer algorithm is used. Through the project we have developed an algorithm for identifying the diabetic retinopathy from fundus images. For identification we have used GLCM features and SVM classifier together. The results indicate a potential for developing an automatic algorithm to segment and trace vessels and diabetic retinopathy classification for planning of treating the disease. For this, we have collected the database of 24 retinal fundus images from Dongaonkar Eye hospital, Kranti chowk, Aurangabad. The proposed system is implemented in MATLAB software.***

Keywords: ***Vessel Segmentation, Graph tracer algorithm, Feature Extraction, GLCM (Gray Level Co-occurrence Matrix), SVM (Support Vector Machine).***

I. INTRODUCTION

Diabetic retinopathy is serious health issue in recent survey. Diabetic disease occurs when insulin level in blood vessels decreases and body is unable to process properly. if diabetic increases then it effect the retina of fundus. And this disease damages the blood vessels and damage the retina. 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. DR is caused by changes in the blood vessels of the retina. Diabetic eye disease is a leading cause of poor vision and blindness.

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Approximately 10% of patients diagnosed with diabetes have vision problems. According to clinical test results, Early detection and treatment may prevent more than 95% of the vision reductions that are observed in diabetic patients. For the patients with diabetes, regular eye examinations will need to obtain proper therapy before it is too late. In biomedical applications, automated retinal image analysis made the detection of retinal pathologies much easier for ophthalmologists. In this paper, a new method is proposed for the identification of diabetic retinopathy using color fundus images. The features are extracted from the image, using the image processing techniques and fed to the support vector machine (SVM) for classification. A typical retina fundus image looks like the one shown in Figure 1. The bright optic disc and the vascular network can clearly be seen in the image.

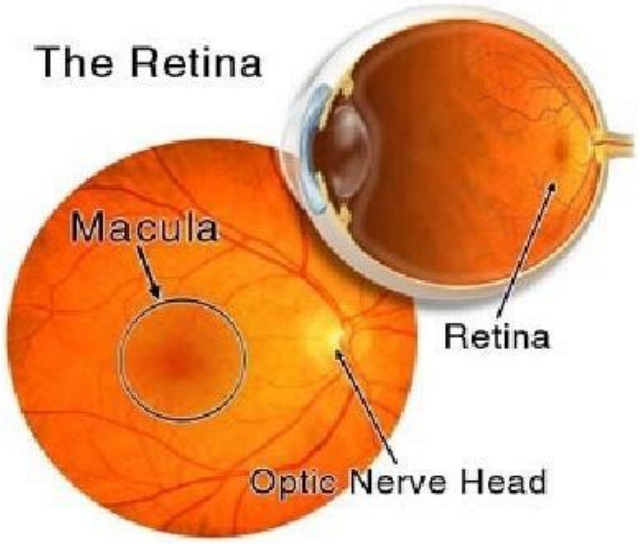

Figure 1: Retina fundus image

DR has mainly four stages:

A) Mild Non-Proliferative Retinopathy- At this early stage, microneurysms may occur. These manifestations of the disease are small areas of balloon-like swelling in the retinas tiny blood vessels.

B) Moderate Non-Proliferative Retinopathy- As the disease progresses, some blood vessels that nourish the retina are blocked.

C) Severe Non-Proliferative Retinopathy- Many more blood vessels are blocked, depriving several areas of the retina with their blood supply.

D) Proliferative Retinopathy-This is the advanced stage, the signals send by the retina for nourishment trigger the growth of new blood vessels. These new blood vessels are abnormal and fragile. They grow along the retina and along the surface.

II. EXISTING SYSTEMS

Different methods for automatic segmentation of retinal images and diabetic retinopathy identification are proposed by different authors. Akarasopharak used FCM clustering technique for detecting the exudates pixels. J. David Rekha Krishnan proposed thresholding technique to identify the lesions, optic disc and vascular network and neural network classifier was then used to assess the severity level of the disease. DU Ning, LI Yafen explains in their work that they had investigated and proposed a computer-based system to identify normal, NPDR and PDR.

R. Vijayamadheswaran et al mainly focused of that work was on segmenting the diabetic retinopathy image and classify the exudates. Segmentation was done using contextual clustering and classification of the exudates was done using radial basis function (RBF) network. Arturo Aquino et al suggested that in that paper, a new automated methodology to detect the optic disc (OD) automatically in retinal images from patients with risk of being affected by Diabetic Retinopathy (DR) and Macular Edema (ME) was presented.

III. PROPOSED METHOD

3.1 Introduction

Here, a new system is proposed for vessel segmentation and diabetic retinopathy classification from fundus retinal images.

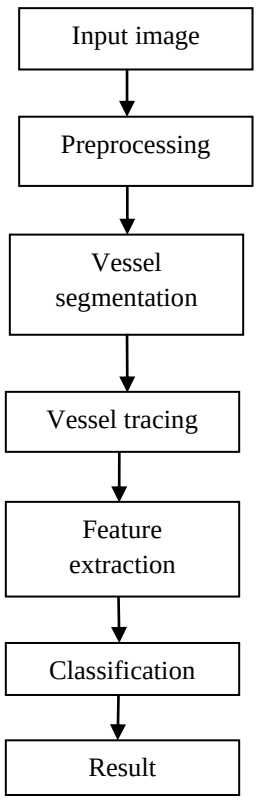

Figure 2: Block diagram of the proposed system

Above figure shows the block diagram of the proposed system. It consists of the following steps.

3.2 Pre-processing

Here, the input images are retinal fundus images in JPEG format . First image selected from the file specified by the string filename. The user has to select the required input fundus image for further processing. Then each image is resized to 256*256. The input image is in RGB format. So it is first converted into gray scale/ green channel image for further processing, in order to facilitate the blood vessel segmentation and to decrease the computational time.

3.3 Post Processing

Post-processing includes following steps:

1) Vessel Segmentation:

Segmentation of retinal vessels is done to identify the early diagnosis of the disease like diabetic retinopathy. Segmentation is the process of separating the foreground regions in the image from the background regions. The foreground regions correspond to the clear retina area containing the vessels, which is the area of interest.

Segmentation divides an image into its constituent regions or objects. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (edge detection). After segmentation, methods of mathematical morphology can be used to improve the results. Thresholding is the simplest and most commonly used method of segmentation. In thresholding, pixels are allocated to categories according to the range of values in which a pixel lies. In this module we segment vessels from the retinal image using thresholding.

2) Vessel tracing:

The structure and properties of the retinal vessels help in the diagnosis of many eye diseases. The major problems in identification of vessels are the uncertainties due to crossover and vessel bifurcation. The graph tracer method is implemented here where the vessel tracking is performed in an accurate manner and the tracking of the vessels are completely done. The tracer starts with the tracking process and continue in the vessel region. When there is any ambiguity during the tracking, a constraint is considered where the angle of the vessel region is identified and further tracking is performed for the vessel region with angle less than 30°. Once the tracking of vessels is completed. Then the identification of crossover and bifurcation is performed where the optimal path of the vessel is identified and displayed. Hence our proposed system concentrates on complete vessel identification, tracking of vessel simultaneously, identification of crossover and bifurcation. During the time of tracking a split of vessel is seen, which is the directional change of segments. When split is not seen as crossover then it is fit as bifurcation and the tracer will follow the paths.

3) Feature Extraction

In this process, total 12 textural features of all images in the database are extracted using GLCM (Gray level co

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occurrence matrix). Then these features are used for diabetic retinopathy classification. GLCM is simply a matrix that gives the sum of the number of times that the pixel with value *i* occurred in the specified.

spatial relationship to a pixel with value *j* in the input image. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest. These GLCM features calculated for some of the images are shown in following table:

Table 1: GLCM features and their values

GLCM features	Image 1	Image 2
Autoc	25.2628	21.6441
Contr	0.2088	0.2049
Corrm	0.9670	0.9617
Corrp	0.9670	0.9617
Cprom	531.1687	365.1736
Cshad	-44.5525	-32.5029
Dissi	0.1542	0.1469
Energy	0.2260	0.2009
Entro	1.9730	1.9505
Homom	0.9297	0.9334
Homop	0.9281	0.9319
maxpr	0.4118	0.3110

Like this, these GLCM features are calculated for all images in database.

GLCM Features

1. Autoc (Autocorrelation):

$$\rho(x,y) = \frac{1}{(L_x - |x|)(L_y - |y|)} \iint_{-\infty}^{\infty} I(u,v)I(u+x, v+y)\,du\,dv \Big/ \frac{1}{L_x L_y} \iint_{-\infty}^{\infty} I^2(u,v)\,du\,dv \qquad |x| < L_x \text{ and } |y| < L_y.$$

2. Contr (Contrast):
It is a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$\sum_{i,j=0}^{G-1} (i-j)^2 P(i,j)$$

3. Corr (Correlation):
It is a measure of gray level linear dependence between the pixels at the specified positions relative to each other.

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y}$$

4. Cprom (Cluster prominence):

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{i + j - \mu_x - \mu_y\}^4 \times P(i,j)$$

5. Cshad (Cluster shade): It is a measure of skewness of the matrix.

$$\sum_{i,j=0}^{G-1} (i + j - \sigma_I - \sigma_J)^3 P(i,j)$$

6. Dissi (Dissimilarity): It gives the measure of much dissimilar are of two neighboring pixels.

$$\sum_{i,j=0}^{N-1} P_{i,j} |i - j|$$

7. Energy (Energy):
It is also known as uniformity of ASM (angular second moment) which is the sum of squared elements from the GLCM. Range = [0 1] Energy is 1 for a constant image.

$$\sum_{i,j=0}^{G-1} P(i,j)\,2$$

8. Entro (Entropy):
It is a measure of randomness. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

$$-\sum_{i=0}^{G-1} p(z_i) \log_2 p(z_i)$$

9. Homom (Homogeneity):
It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1 + (i-j)^2} P(i,j)$$

10. maxpr (Maximum probability):
This simple statistic records in the centre pixel of the window the largest P_{ij} value found within the window. max(i,j)P(i,j)

3.4 Diabetic retinopathy classification

After extracting GLCM features of images, Diabetic retinopathy classification is carried out. For this, we have used SVM (Support vector machine) classifier. This classifier must be trained first. For training we have used 9 images out of which 3 images are used for normal class training, 3 images are used for exudates class training and next 3 images are used for training NPDR class. The GLCM features are given as input to SVM. Each image is assigned a class i.e. for normal, class 0 and for exudates, class1and for NPDR, class 2. Support Vector machines (SVM) are a set of supervised learning tools applied for data classification and regression. SVM model maps the training samples that are the points in features space into different categories which are clearly separated with the widest gap in between them. The testing samples are mapped to the same feature space and classified as belonging to any of the classes. SVM constructs an

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optimal hyper plane that would maximize the margin of separation between the classes. The feature vectors that lie close to the margin are called the support vectors. Figure 3 depicts the svm classifier with the optimum hyperplane. A binary SVM finds an optimum hyper plane which separates the feature vectors of the two classes with largest margin from the hyper plane.

The separating hyper plane is of the form w.x+b=0, where w is the norm. If the data is linearly separable, the maximum margin of separation is found by the minimization of the function E=|| w2 ||.

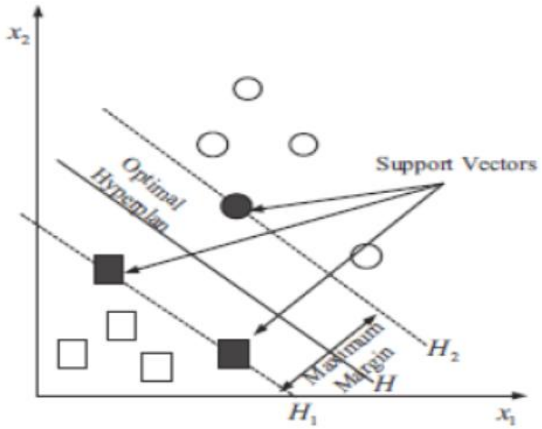

Figure 3. SVM classifier with optimum hyper plane

If the training data is non-linear, then input space would be mapped to a higher dimensional feature space H through the mapping φ. As an extension to binary SVM as classifier, multi class approach to classification problem is developed. The general methods are one-against-one, one-against-all and global method. In the current work, one-against-all approach is used, in which a collection of binary classifiers is used, and one classifier separates a class from the remaining ones with the largest margin. The training data is chosen to be statistically significant, such that during training the training set analyzes the data into different classes.

3.6 System flowcharts

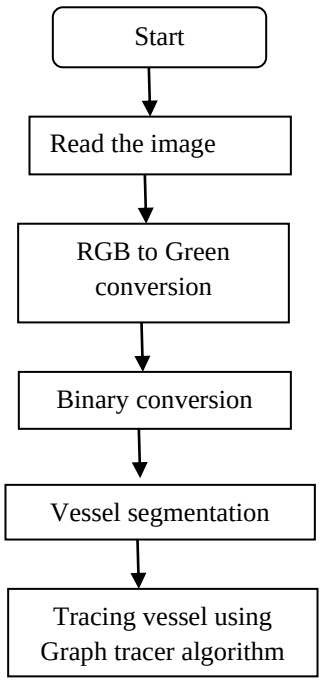

Figure 4: Flowchart for vessel tracing

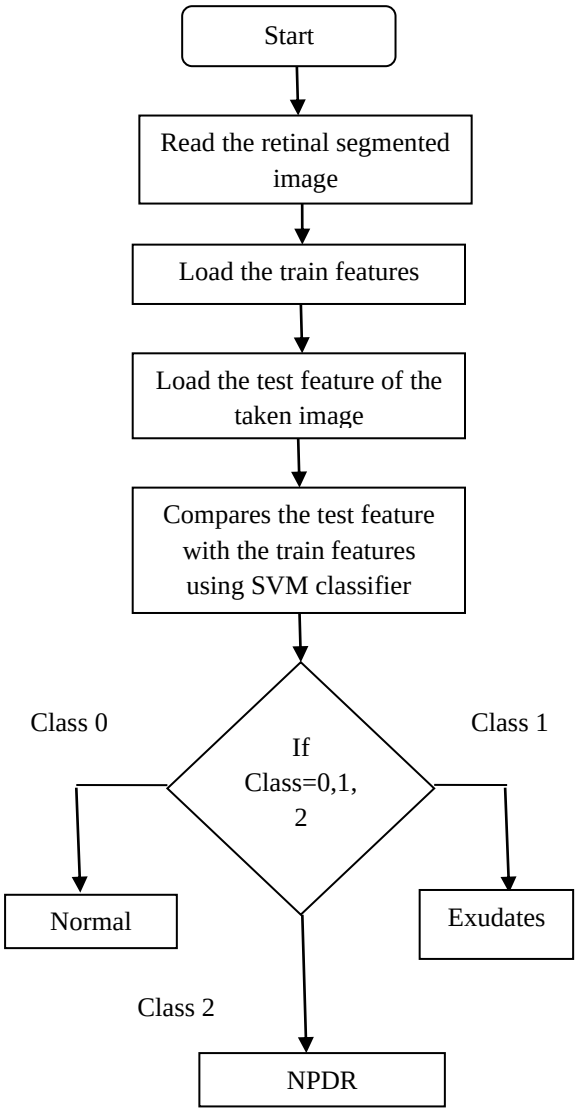

Figure 4: Flowchart for Diabetic retinopathy classification

3.7 Database

We have taken the database of fundus images which are collected from Dongaonkar Eye Hospital located at kranti chowk, Aurangabad. All these images are in JPEG format. Some images from the database are shown in following figure:

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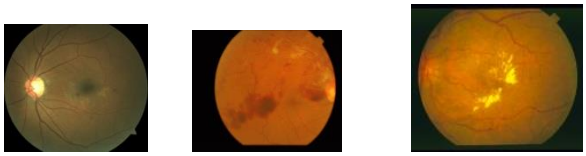


(a) (b) (c)

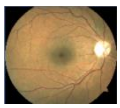
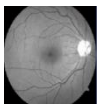
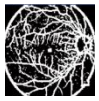
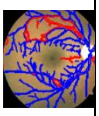
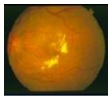
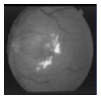
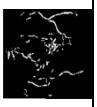
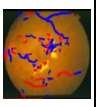
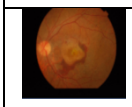
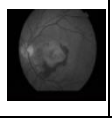
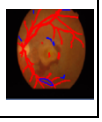
Figure 5: Images from database

IV. RESULTS OF EXPERIMENTATION

The databases have been used for analyzing the performance of algorithms used for automated diagnosis of diabetic retinopathy. The images were acquired from Dongaonkar Eye Hospital, Aurangabad.

The database consists of 24 images of which 7 images are normal and 11 are exudates and 6 are NPDR. The input images are classified as belonging to normal, Exudate or NPDR classes using multiclass SVM classifier.
In this section, the results of the proposed system are shown for four images from the database.

Table 2: (a) Input image, (b) Green channel separation, (c) Binary conversion, (d) Vessel segmentation, (e) Vessel tracing

Input image	Green channel separation	Binary conversion	Vessel segmentation	Vessel tracing
				
				
				

Similarly, the results for all images in the database are obtained.

4.1 Parameters for Performance Evaluation of the classifier

The evaluation of the performance of the classifier is done by calculating the parameters such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP is the number of abnormal images classified as abnormal by the screening system. TN is the number of images that are really normal and classified as normal by the screening procedure. FP is the number of normal images that are predicted to be abnormal and FN is the number of abnormal images, classified by the procedure to be normal. Using these parameters, Sensitivity, Specificity and accuracy are calculated.

Sensitivity is the measure of percentage of abnormal images classified by the screening procedure.
sensitivity = TP/(TP+FN) × 100

Specificity is defined as the percentage of normal images classified by the system.
specificity = TN/(TN+FP) × 100

Accuracy is the percentage of correctly classified normal and abnormal images.
accuracy = (TP+TN)/(TP+TN+FN+FP) × 100

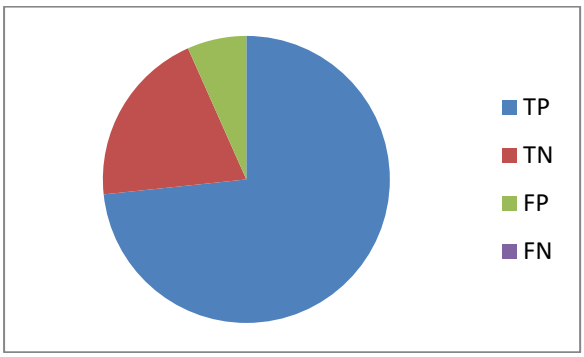
Following are the results for classification into three categories such as normal, NPDR and PDR after training and testing with images of each category.

TP = 11
TN = 3
FP = 1
FN = 0

Sensitivity = TP/(TP+FN) × 100
= 11/(11+0)
= 100%

Specificity = TN/(TN+FP) × 100
= 3/(3+1)
= 75%

Accuracy = (TP+TN)/(TP+TN+FN+FP) × 100
= (11+3)/(11+3+0+1)
= 93.33%



Graph 1: Accuracy parameters

Thus, from the results we found that our proposed system has achieved 93.33% accuracy, specificity of 75% and better sensitivity i.e. 100%.

V. CONCLUSIONS

Thus it can be concluded that the proposed method performs well. The system gives results within few seconds. The SVM used for diabetic retinopathy classification has improved accuracy. Thus, this approach is a potential for developing an algorithm to vessel tracing and diabetic retinopathy identification for surgical planning of treating disease. This system intends to help ophthalmologists in the screening process to detect symptoms of Diabetic

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Retinopathy quickly and more easily. This can be a preliminary diagnosis tool or decision support system for ophthalmologists. The system intends to help the ophthalmologists in the diabetic retinopathy screening process to detect symptoms faster and without doubt The SVM classifier achieved an average accuracy of 93.33%.

VI. FUTURE SCOPE

The vessel tracing and diabetic retinopathy classification has very wide scope since it reduces manual work and also computational time. Also it can be useful for diagnosis of other eye diseases. The million order dataset can be selected and image classification can be done on larger dataset.

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