Diabetic Macular Edema Detection using Graph Theory and Retinal Layer Features

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Abstract*: Diabetic Mellitus is a disease which can affect the functioning of different organs in the body such as heart, kidney, retina etc. When this disease affects the eye it leads to a condition called Diabetic Retinopathy and this disease in turn may lead to a disease called Diabetic Macular Edema (DME). If DME is left untreated it may lead to vision loss. In this work, a method of automated detection of DME from retinal images has been proposed. Retinal layer in the Optical Coherence Tomography (OCT) images are first segmented using graph based method. Then, a set of 30 features are extracted from the retina and this has been given to different forms of Support Vector Machine (SVM) for the classification purpose. SVM with polynomial order 2 gives the best result with 96.66% accuracy.*

Keywords— *Diabetic Macular Edema, Optical Coherence Tomography, Graph Theory, Retinal features, Support Vector Machine.*

I. INTRODUCTION

Retina is a thin layer of light sensitive tissue at the back of the human eye. Central part of the retina is called as macula which is responsible for the detailed central vision. Retina can be affected by diseases which may not be directly related to the eye. Diabetic Retinopathy (DR) is one such disease. If DR is left untreated it may lead to leakage of blood vessels and accumulation of fluids in the macular region leading to formation of Macular Edema. Macular edema is most commonly classified into either being clinically significant or not. Clinically significant macular edema (CSME) is defined as DME [1]. DME leads to loss of central vision. About 50% of the people with diabetes are found to be affected by Diabetic macular edema (DME) and it is the largest cause of vision loss in diabetes [2]. DME can be detected using retinal images acquired using Fundus Imaging, Fundus Fluorescein Angiography (FFA) and Optical Coherence Tomography (OCT). OCT has the capability to detect DME at an earlier stage. OCT is an imaging technique similar to ultrasound scanning, but instead of Ultrasound signal, light rays are transmitted through the pupil and reflected light is detected using a detector. Reflected light is color coded to indicate depth of penetration. Optical Coherence Tomography can provide reliable thickness measures over repeated scans [3]. It can produce cross-sectional images of structures in retina which is reliable. These images can be quantitatively analysed for disease detection.

Namita Sengar et al. [4] have graded Macular Edema by dividing the fundus image into regions based on international standard. They have located macula using adaptive method. Severity of the disease is found based on scaling of bright lesions in the macular region. This method has achieved an accuracy of 80 to 90%. Aditya Kunwar et al. [5] have detected high risk macular edema region by considering a region of radius 1DD around the macula. This region is found to cover exudates present in high risk region with good accuracy. They have tried to reduce the computational time without compromising accuracy of detection. Pratul P. Srinivasan et al. [6], have proposed SD – OCT based method that uses feature vectors extracted from multiscale histograms of oriented gradient descriptors and have classified it using support vector machine. The algorithm has been found to be useful for remote diagnosis of ophthalmic diseases. Umer Aftab et al. [7] have developed an automated system for detection of exudates color fundus images. They have created a binary map for the candidate exudates region using Gabor filter band. The images have been classified using gaussian mixture model. M. Usman Akram et al. [8] have proposed a system for accurate detection of macula using a detailed feature set and GMM based classifier. They have also developed a hybrid classifier which is a combination of GMM and SVM. This method has improved accuracy in exudate detection. A dual scale gradient information based segmentation of macular region in OCT images has been used by Qi Yang et al. [9] and it has been found to give good accuracy and reproducibility. Macular Edema has been assessed by a fully automated method using Discriminant Analysis Classifier in a work by Bilal Hassan et al. [10].

In this work a method has been proposed for the detection of Diabetic Macular Edema using Retinal features extracted from OCT images. OCT images are first preprocessed to make it suitable for segmentation. A graph based method is applied to

segment the retinal layers. The segmented image is divided into 5 Regions and then regional thickness features are extracted. GLCM based features are also extracted along with the thickness measure and finally images are classified by giving these features to SVM classifier.

II. Diabetic Macular Edema (DME) Detection Method

OCT images are used in this work for the detection of DME. Methodology used is given as a block diagram in Fig.1. The input images which are in RGB format are first converted to gray scale images. These images are then filtered and smoothened by using a median filter of size 5x5.

A. Segmentation

The retina has ten layers. Out of these ten layers, Inner Limiting Membrane (ILM) and Retinal Pigment Epithelium (RPE) have been segmented and plotted using the method suggested in [11]. In this method of segmentation, each OCT image is represented as a graph of nodes and each pixel is considered as a node. Edges are the links connecting the nodes. A path is formed by a set of connected edges that can be used to traverse across the graph. Weights are assigned to edges using the equation (1), in order to make each pixel different from its neighboring pixel. Preferred path between the start node and end node is obtained by selecting the route in which total weight sum is at a minimum value. This path is used to separate the regions.

$$w_{ab} = 2 - (g_a + g_b) + w_{min} \quad \ldots (1)$$

where,
w_{ab} is the weight assigned to the edge connecting nodes a and b,
g_a is the vertical gradient of the image at node a,
g_b is the vertical gradient of the image at node b,
w_{min} is the minimum weight in the graph which is a small positive number added for system stabilization. between 0 and 1 and $w_{min} = 1 \times 10^{-5}$. The lowest weighted path of a graph between arbitrary end points can be determined using efficient techniques called Dijkstra's algorithm [12]. Finding minimum weighted path using Dijkstra's algorithm requires weights to be in the range 0 to 1. Zero indicates unconnected node pair. Matrix containing graph weights is defined as the Adjacency Matrix of a graph. Estimation of start and end nodes are required for the segmentation of the specific layer. One extra column of nodes is added to left and right side of the image with random gray values and minimal weights w_{min} are given to edges in the vertical direction. Value of w_{min} must be very much smaller than any of the non zero weights in the adjacency matrix of the original image (or graph). These two additional columns are removed after the segmentation of the layer is complete after applying Dijkstra's minimum weight path algorithm.

After the segmentation of first layer the search space can be limited and the process can be repeated to segment a new boundary. Therefore the retinal layers can be iteratively segmented by the order of prominence. Detailed explanation of segmentation method can be found in [11] and [12]. The result of segmentation with ILM and RPE layers marked is shown in Fig.2.

B. Feature Extraction

Two types of features are extracted from the segmented OCT images. First type is the thickness features extracted from segmented OCT images. Second one is the textural features extracted from GLCM of the OCT images.

1). Thickness Features: Occurrence of macular edema causes change in the thickness of the retinal layer. In this work, a set of values related to thickness of the region between ILM and RPE are extracted for the detection of macular edema. The thickness values determined over the entire layer are

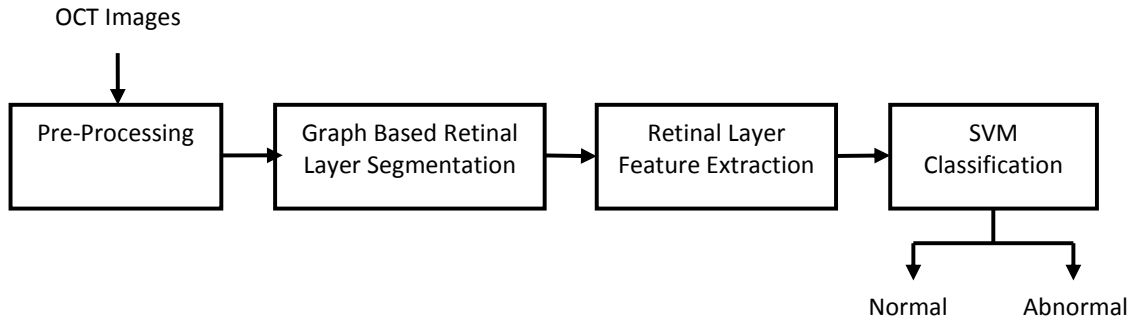


Fig.1. Methodology

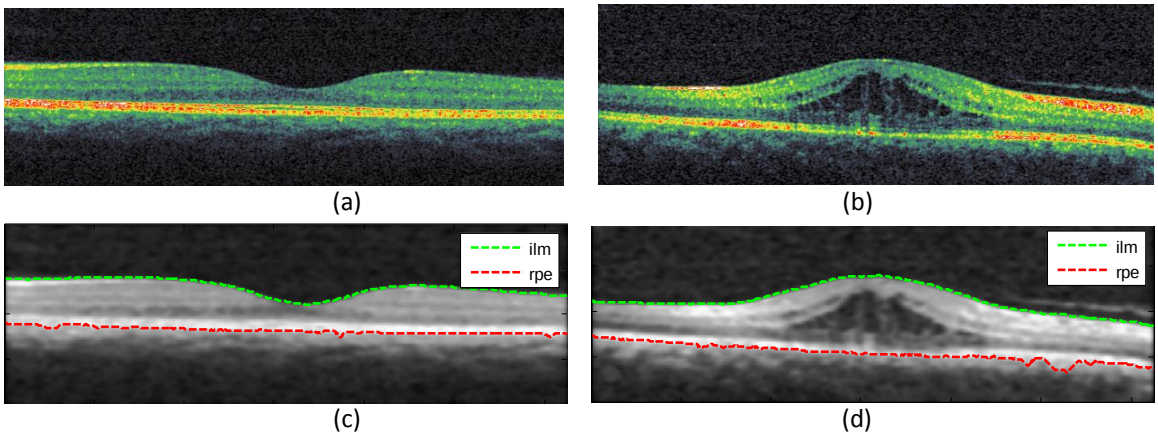


Fig. 2. a) Normal Image, b) DME Image, c) ILM & RPE layers marked in normal image
d) ILM & RPE layers marked in DME image

- Average thickness (T_{avg}),
- Maximum thickness (T_{max}),
- Minimum thickness (T_{min}),
- Difference thickness ($T_{diff} = T_{max} - T_{min}$)

Difference in the average thickness value, when taken over the entire layer, did not show much variation between normal and DME images therefore the above mentioned parameters are extracted by splitting the OCT images into five equal regions also as shown in the Fig.3. This is done due to the fact that the average thickness difference between normal and DME image, in the foveal region is comparatively more than the average thickness of the entire retinal layer. This can be clearly seen in the plots given in Fig.4. Therefore a total of 24 thickness features are extracted from each image.

2) Textural Features: Texture is an important component perceived by human visual system. A set of Gray Level Co-occurrence Matrix (GLCM) based texture features has been introduced [13] in the year 1973. These features are also called Haralick features and they are widely used in medical image analysis applications. In this work, we have extracted six textural features namely, Energy, Contrast, Correlation, Variance, Entropy, and Homogeneity. The equations are as given below.

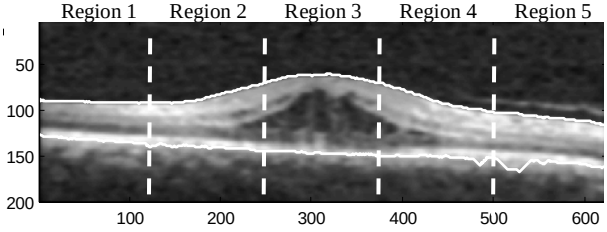


Fig.3. Segmented Image Split into 5 Equal Regions

- Energy which is obtained from Angular Second Moment (ASM) gives information about local uniformity of the gray levels.

$$\text{Energy} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} p(i,j)^2 \quad \text{...(2)}$$

- Contrast gives a measure of gray level changes between two pixels.

$$\text{Contrast} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} |i-j|^2\, p(i,j) \quad \text{...(3)}$$

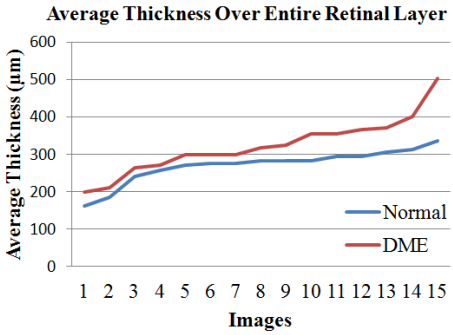
- Correlation indicates linear dependency of gray values in co-occurrence matrix:

$$\text{Correlation} = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \frac{(ij)\, p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad \text{...(4)}$$

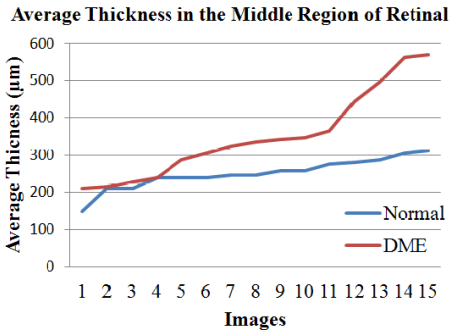
where μ_x, μ_y and σ_x, σ_y are the means and standard deviations.

- Entropy gives information about amount of randomness in image.

$$Entropy = -\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} p(i,j)\log(p(i,j)) \quad \text{...(5)}$$



(a)



(b)

Fig.4. Average Thickness Plots

- Homogeneity indicates closeness of GLCM elements distribution and the diagonal of GLCM.

$$Homogeneity = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{p(i,j)}{1+(i-j)^2} \quad ...(6)$$

- Variance measures the variation in intensity distribution

$$Variance = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(i-\mu)^2\, p(i,j) \quad ...(7)$$

Where $p(i,j)$ is the $(i, j)^{th}$ element of the normalized GLCM of size MxN

C. Classification

A set of 30 features that have been extracted are given to SVM for the classification of images as normal or abnormal. Support Vector Machine a supervised learning technique is used for classification. In SVM, each feature is transformed as a point in n-dimensional space. Here n is the number of feature vectors used and feature value is used as value of a particular coordinate. Classification is done by finding the hyper-plane that differentiates the two different classes by a large margin as shown in Fig.5. Co-ordinates of individual observation are called as Support Vectors.

Classification using SVM involves separating data into training and testing sets. Each instance in the training set contains one target value and several features. SVM aims at generating a training data based model which can predict target values of the test data when the test data features alone are given.

If we take a training set with label pairs (x_i , y_i), $i = 1, \ldots, l$ where $x_i \in R^n$ and $y \in \{1, -1\}^l$, the support vector machines [14] find the solution to optimize the problem given below [15].

$$\underset{w,b,\xi}{min}\ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i \quad ...(8)$$

Where
w – Weight Vector
b – Bias
ξ – Degree of misclassification
C – Penalty parameter of the error

Subject to $y_i\,(\mathbf{w}^T(x_i) + b) \geq 1 - \xi_i$, ...(9)

Where $\xi_i \geq 0$

In SVM, training vectors x_i are transformed into a higher dimensional space by the function φ. SVM finds a hyperplane that separates the vectors with maximal margin. $C > 0$ is the penalty parameter of the error and $K(x_i , x_j) \equiv \varphi(x_i)^T \varphi(x_j)$ is the kernel function. The two basic kernels used in this work are

- Linear: $K(x_i , x_j) = x_i^T x_j$ . ...(10)
- Polynomial: $K(x_i , x_j) = (\gamma\, x_i^T x_j + r)^d$, $\gamma > 0$. ...(11)

Where, γ, r and d are the kernel parameters

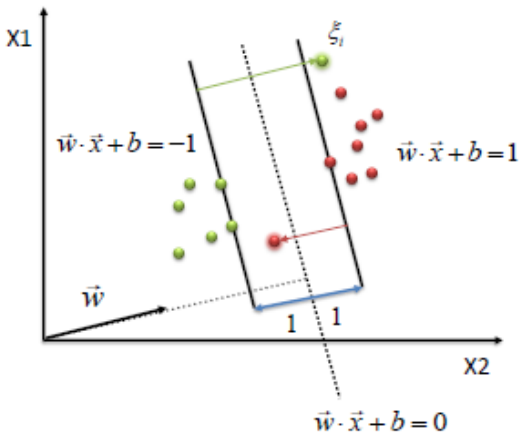


Fig.5. SVM Classification

III. Experimental Results

OCT images required for this work has been collected from Sushrutha Eye Hospital, Mysuru, Karnataka, India. The data set used in this work consists of 46 OCT images out of this 26 are normal images and remaining 20 are images with abnormality (i.e., affected by DME).

SVM is trained using 38 images in which 23 are normal images and 15 DME images. During testing 30 images were used consisting of 15 normal and 15 DME images. Output of the classifier is evaluated based on the values of

- **True Negative (TN)** – Number of normal images predicted as normal.
- **True Positive (TP)** – Number of abnormal images predicted as abnormal.
- **False Positive (FP)** – Number of normal images predicted as abnormal.
- **False Negative (FN)** – Number of abnormal images predicted as normal.

Using these values the following performance measure are calculated.

- **Sensitivity (Sn):** Measure of correct predictions of presence of abnormality in the image out of total number of images with abnormality. It is also called as True Positive Rate.

$$Sensitivity = \frac{TP}{(TP+FN)} X\ 100 \quad \ldots(12)$$

- **Specificity (Sp):** Measure of correct predictions of absence of abnormality in the image out of total number of images without abnormality. It is also called as True Negative Rate.

$$Specificity = \frac{TN}{(FP+TN)} X\ 100 \quad \ldots(13)$$

- **Accuracy (A):** Measure of correct predictions of presence or absence of the abnormality in the image out of total number of images.

$$Accuracy = \frac{TP+TN}{(TP+FN+FP+TN)} X\ 100 \quad \ldots(14)$$

- **Misclassification Rate (MCR):** Measure of wrong predictions.

$$MCR = \frac{FP+FN}{(TP+FN+FP+TN)} X\ 100 \quad \ldots(15)$$

Classification has been done using Linear SVM, SVM with polynomial kernel of order 1 and order 2. Best result of classification was given by SVM with polynomial kernel of order 2. Confusion matrix of the best result is given in Table I. and performance measures obtained are tabulated in Table II.

TABLE I
CONFUSION MATRIX OF SVM WITH POLYNOMIAL OF ORDER 2

	Object Predicted Absent	**Object Predicted Present**
Object Actually Absent	True Negative (TN) **15**	False Positive (FP) **0**
Object Actually Present	False Negative (FN) **1**	True Positive (TP) **14**

TABLE II
CLASSIFICATION RESULTS

SVM	**Sn (%)**	**Sp (%)**	**A (%)**	**MCR (%)**
Linear	86.66	100	93.33	6.66
Polynomial Order 1	86.66	100	93.33	6.66
Polynomial Order 2	93.33	100	96.66	3.33

Receiver Operating Characteristic Curve for SVM classification using Linear and Polynomial Kernel of order 2 are shown in Fig.6. ROC Curve is a graphical indication of how well a binary classifier can diagnose a problem. It is plotted as Sensitivity vs Specificity.

IV. Conclusions

In this work a method for the detection of Diabetic Macular Edema (DME), which is a common cause of loss of vision in people with diabetes has been developed. Proper segmentation of retinal layers is very important for extracting accurate values of retinal layers. This has been achieved by using Graph based method for the segmentation of ILM and RPE of the Retina. Diabetic Macular Edema appears prominently in the foveal region therefore extracting retinal layer thickness over the entire layer did not show much difference between normal and DME images. Hence, features have been extracted by splitting the segmented image into five equal regions. A set of 30

features have been extracted and it has been classified using different forms of SVM.

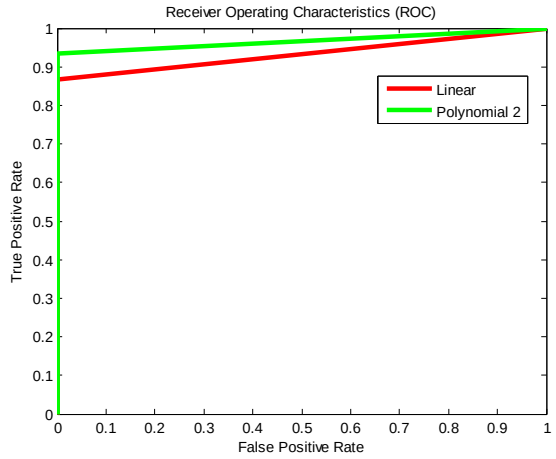


Fig.6. Receiver Operating Characteristics (ROC) Curve

Performance measures of classification shows that SVM with polynomial kernel of order 2 gives the highest accuracy of 96.66% and smallest misclassification rate of 3.33%.

Accuracy may be improved by using more number of images. Accuracy can further be improved by extracting more number of discriminant features from the retinal layer. The features extracted can be tested with other types of classifiers also in order to choose the best classification technique for the proposed work.

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