

AUTOMATIC DETECTION OF DIABETIC MACULAR EDEMA FROM B-SCAN OCT IMAGES BASED ON PATTERN CLASSIFICATION TECHNIQUES

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Received 14 June 2018 • Revised 23 August 2018 • Accepted 24 September 2018

Abstract: *Objective-* This paper presents an automatic detection method to find the changes in thickness of the layers of retina from Optical Coherence Tomography (OCT) B-Scan images for resulting detection of Diabetic Macular Edema (DME) in diabetic patients.

Methods- In this study, using image processing methods initially the images are cropped according to the region of interest, followed by conversion from RGB to gray scale, and then median filtered method is used to de-noise them. Then, the six retinal layers are segmented using Graph-Cut Search method. Region of interest is performed on the Optical Coherence Tomography (OCT) scan and the automated retinal layers thickness measurements between the every two layers of the macula in the regions are determined. Area enclosed between the every two layers is also estimated. Local Binary Pattern (LBP) local texture features are extracted from segmented B-SCAN OCT images that are subsequently trained and tested by Support Vector Machine (SVM) and Cascade Neural Network(CNN); which are two different machine learning classifiers to classify whether the OCT image is normal or DME affected. In this study, 55 datasets of OCT images (25 normal and 30 DME) were used for classification.

Results- The performance results of both the classifiers are compared with respect to sensitivity, specificity, accuracy, precision and F-Score. On comparison of these two classifiers the CNN classifier was better learns faster, highest accuracy than of SVM classifier, it has a sensitivity of 95%, specificity of 100%, accuracy of 96%, precision of 100% and F-Score of 97%.

Conclusions- Thus, this algorithm can be used by ophthalmologists for early detection of Macular Edema.

Keywords: Diabetic Macular Edema (DME), Graph-Cut Search method, Local Binary Pattern (LBP), Optical Coherence Tomography (OCT), Support Vector Machine (SVM). Cascade Neural Network (CNN).

INTRODUCTION

The macula is the central part of the retina and responsible for the visual acuity and color vision. Any swelling or fluid build-up in this portion of retina due to leaking of surrounding abnormal capillaries called as microaneurysms is called Diabetic Macular edema (DME). DME is most common causes of vision loss in individuals with diabetes in the initial stage if detected early and treated correctly. This same DME results in irreversible vision loss if treatment is delayed, and a cause of significant loss of productivity among diabetic patients. DME is defined as the increase in retinal thickness within one disc diameter of the foveal center with or without presence of hard exudates. Hence there is need to prevent the vision loss due to DME by early diagnosis by using OCT and classifying the type of edema and starting the required treatment [1]. Using the Optical Coherence Tomography (OCT) images, the doctor can decide the status of the patient with disease or not.

The B-SCAN OCT is a non-invasive, non-contact, no-radiation, painless and fast diagnostic imaging tool used in ophthalmology for diagnosis and visualizing the cross sectional layers of the retina to detect a variety of retinal diseases [2], which is important for assessing the response to treatment. Spectral Domain OCT (SD-OCT) [3] images the depth of the retina with a high resolution and fast image acquisition is an adequate tool, compared to fundus images for DME identification [4].

This paper focuses on detection of Diabetic Macular Edema from OCT images using an algorithm developed in MATLAB. The retina OCT images layers are segmented based on graph-cut search method and the retinal layers thickness measurement is evaluated for the detection of normal or DME affected diseases images. The area enclosed between the every two layers is estimated for all the images. Further, a few textural local features of the image are extracted. The classification between normal and DME diseased images is classifying using Support Vector Machine (SVM) and Cascade Neural Network (CNN) classifiers.

METHODOLOGY

The methodology of the proposed work is discussed in the following sequence as shown in diagram of Figure 1.

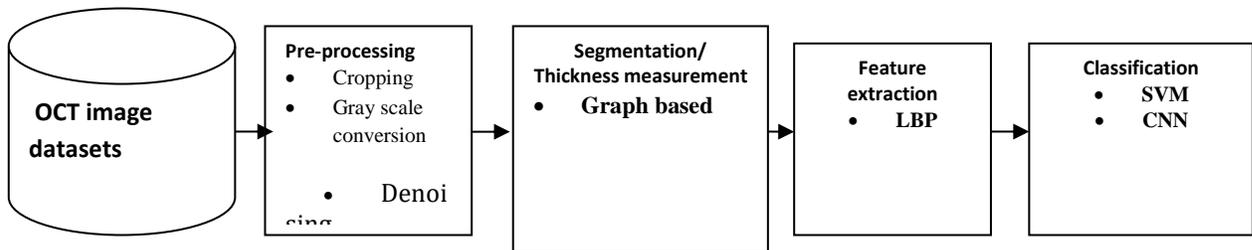
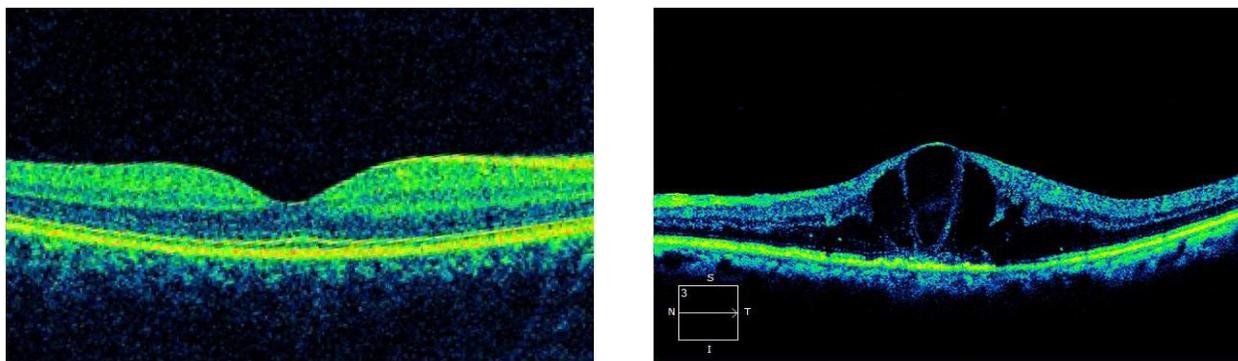


Fig 1: Methodology for DME diseases detection

2.1 Input Retinal OCT Images

A total 150 OCT images (40 normal and 110 DME) data sets were obtained from Jyoti Eye Care Hospital, Puducherry. The following figure 2 (a) and (b) shows the normal and DME affected of original OCT images of retina.



(a)

(b)

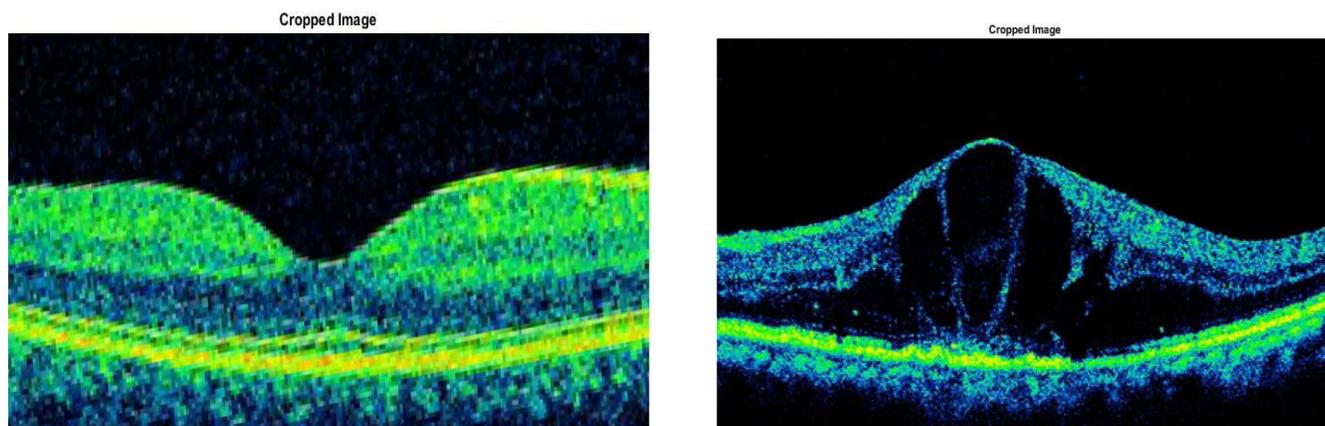
Fig 2: Original OCT image of (a) Normal image (b) DME affected image

2.2 Pre- Processing

The OCT images are pre-processed first through cropping the images to include only the region of interest, then secondly converting from RGB to Grey scale conversion and lastly reducing the noise removal to have a smooth image using image processing methods.

2.2.1. Cropping OCT Images

Before further processing for detection and classification of OCT images, it is necessary to crop each OCT image with only the region of interest (ROI) remaining by eliminating the undesired regions to focus on the areas where DME affected disease is most likely to be present. The cropped OCT image of normal and DME disease is shown in Figure 3 (a) and (b).



(a)

(b)

Fig 3: Cropped OCT image of (a) Normal (b) DME affected

2.2.2. Grey Scale Conversion and Denoising

The original input OCT images are in RGB format. In this study, after cropping the RGB image is converted into grayscale. The gray-scale image is shown (a) and (b) in Figure 4. The OCT images are corrupted by speckle noise during the imaging process which reduces the efficiency of the classification results. In this work, to obtain a better quality, the image is processed before feature extraction by using median filter [5] of window size 5*5 denoising method. Thus removing the speckle noise in the ROI portion and smoothing of the retinal OCT images. The filtered image is shown (a) and (b) in Figure 5.

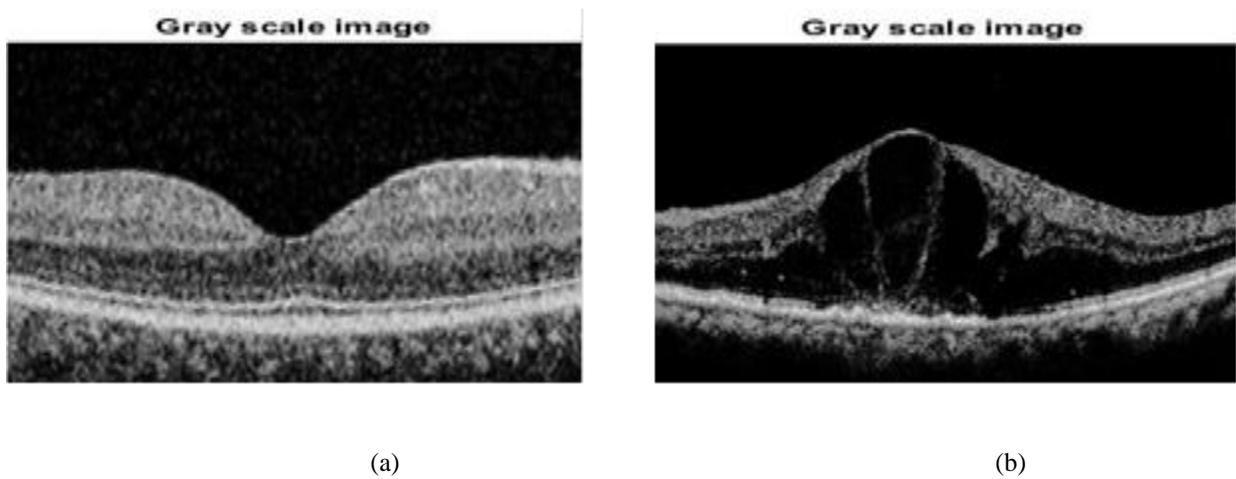
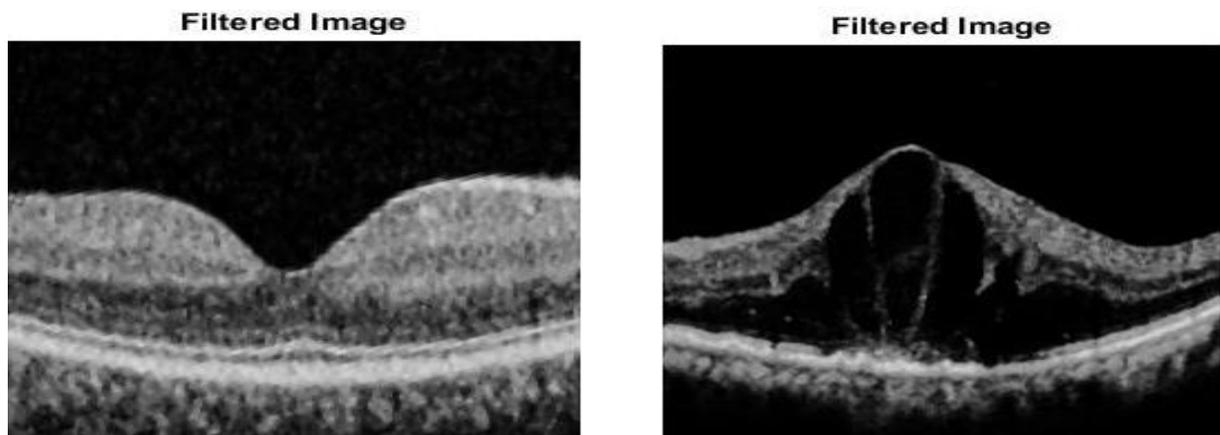


Fig 4: Gray scale OCT image of (a) Normal (b) DME affected



(a) (b)

Fig 5: Median filtered OCT image of (a) Normal (b) DME affected.

2.3. Segmentation of retinal layers

In this work, before extracting the features from cropped retinal OCT images for classification, segmentation of retinal layers is necessary for extraction of accurate feature values. So, firstly automatic segmentation of six retinal layers in OCT images of normal and DME affected are implemented. The segmented six retinal layers are

- | | |
|--|--------------|
| (1) Inner Limiting Membrane (ILM) to Nerve Fibre layer(NFL) | (ILM-NFL) |
| (2) Nerve Fibre layer (NFL) to Ganglion Cell Layer (GCL) | (NFL-GCL) |
| (3) Ganglion Cell Layer (GCL) to Inner Plexiform layer (IPL) | (GCL) – IPL) |
| (4) Inner Nuclear Layer (INL) to Outer Plexiform layer (OPL) | (INL – OPL) |
| (5) Outer Plexiform layer (OPL) to junction of Inner Segment and Outer Segment(ISOS) | (OPL-ISOS) |
| (6) Inner Segment/Outer Segment(ISOS) to Retinal Pigment Epithelium (RPE) | (ISOS – RPE) |

The OCT images are segmented based on graph-cut search segmentation method and dynamic programming method[6], to reduce the processing time for segmentation of layers of OCT image and feature extraction. In this segmentation method, many algorithms are combined such as the graph gradient, intensity information, etc. to find the shortest path and thus results obtained[7]. This decreases the search region and has shown to be a fast and reliable method for retinal layer segmentation. The algorithms are implemented on MATLAB.

Graph theory is used for processing segmentation of cropped OCT images, in which OCT images are a set of nodes and pixel is represented as nodes. The links connecting nodes are called edges. The connected edges form a layer and edges were detected by the graph search algorithm. A set of edges with connected weight is a path used to travel across the graph from a start node to an end node. Weights are assigned to edges using the following equation(1), in this each pixel different from its neighbouring pixel. To travel across the graph from one node to another, then the path is selected with a total weight sum with minimum value. This resulting selected path segments one region from another and by the order the process can be iteratively repeated to create the segmented retinal layers. In this problem boundary between retinal layers correspond to the preferred paths on an OCT images.

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

Where

w_{ab} is the weight assigned to edges connecting nodes a & 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, a small positive number added for system stabilization.

In the equation (1) the low weight values to node pairs with vertical gradients. The weights will vary between 0 and 1. The implementation for segmenting the layers in OCT images results in two undirected adjacency matrices, sensitive to dark-to-light or light-to-dark transitions. In this experiment Dijkstra's shortest path search algorithm [8] method is used to find the lowest-weighted path initialized at the upper left and the bottom right pixels of the image and divide the image graph into layers. The resulting path shows all six layers of the OCT image. The necessary layers are then plotted. The result of segmentation of layers of normal and Cystoid Macular Edema OCT images and plots of the layers is shown (a) and (b) in Figure 6. The layers are represented by different colors respectively.

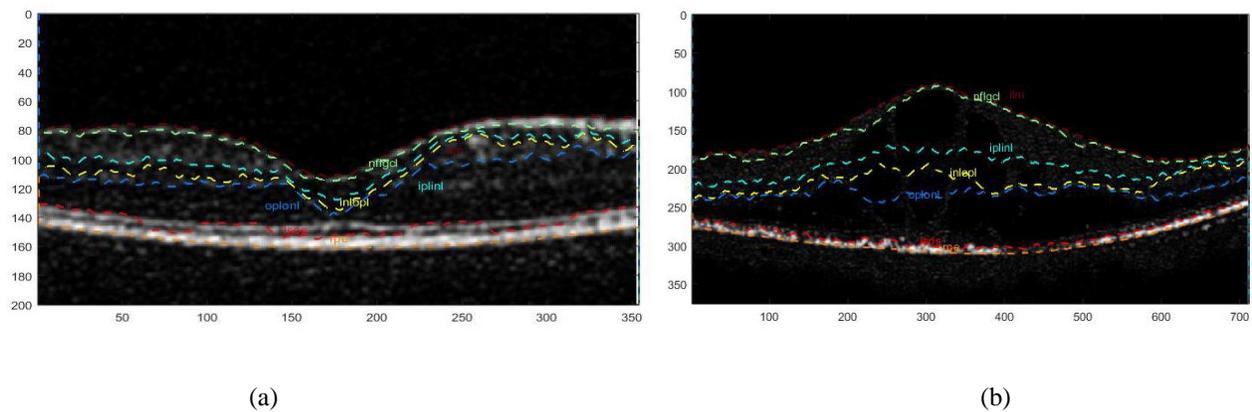


Fig 6: .Example of layers Segmentation of OCT images of (a) Normal and (b) Cystoid Macular Edema.

2.4. Thickness Evaluation

The different retinal layer at the fovea and para fovea regions are thus measured by the distance between the layers segmented and unit of measurement is in microns for the detection of DME affected diseases in OCT images. Thickness measurement can be used to differentiate from normal and DME affected subject. We have seen the thickness measure of the foveal region is comparatively higher for the images that have inflammation macular edema and lesser for normal images. Due to the inflammation of the macula in case of Diabetic Macular Edema, the area enclosed by these every two layers is comparatively larger than the same in case of normal eye. The results of the segmentation of between layers (Figure 6) are considered as the curves representing the layers. Using Area Under the Curve (AUC) technique, the area between the every two layers was estimated and this metric is used as one of the parameters to train the classifier.

After retinal layers are segmented, next the thicknesses of the segmentation of six retinal layers for each of the 55 OCT images between every two neighbouring layers boundaries are calculated and determined. In this work, thickness of the entire OCT images was evaluated. Retinal thickness was automatically calculated by using automatic segmentation method in MATLAB. The average difference in layer thickness automatic estimates was computed for between every two layers of each OCT images. Measurements were displayed as the mean and standard deviation for each of the layers. The mean and standard deviation in the segmented six retinal layers thickness measurements of these differences for normal and abnormal OCT images were calculated are shown in Table 1. Column I shows the absolute average thickness difference for the various retinal layers as measured of normal OCT images for 20 OCT images. Column II displays the retinal layer thickness difference calculation for the 35 OCT images of DME affected OCT images.

Among the 55 OCT images one DME patient's left eye(OS) Macular thickness is examined clinically by the OCT scan and its OCT scan images ,thickness map, fundus image and thickness values shown below in figure 7 and using automated segmentation algorithm in MATLAB the mean and standard deviation segmentation retinal layers thickness are shown in Table 1.

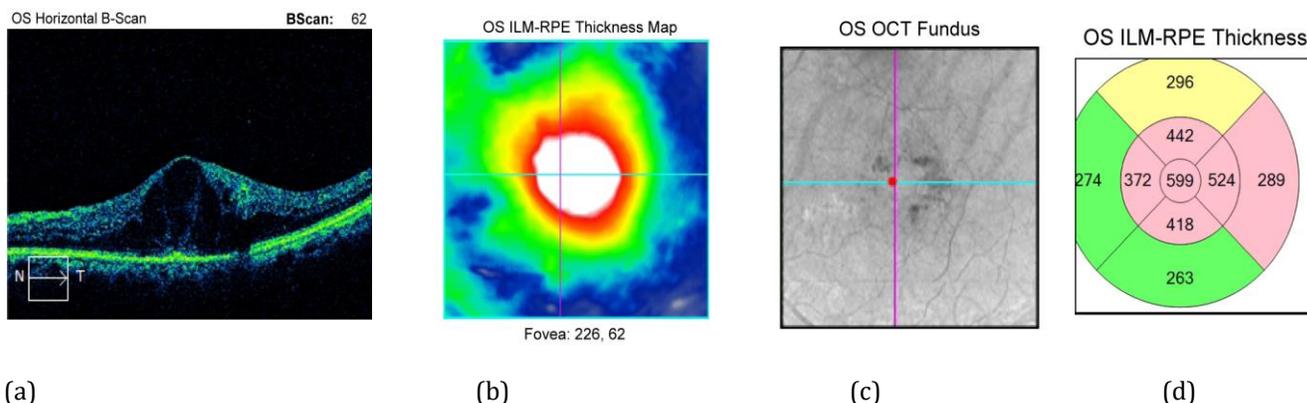


Fig. 7: Macular thickness OCT B-Scan DME patient right eye(OS)'s (A)OCT image , (B) thickness map,(c) the fundus image and(B) Thickness value

Table 1: Differences of Retinal layers thickness measurement segmented OCT images of (a) Normal and (b) DME affected images

		Segmented Retinal layers thickness measurements of Normal and Cystoid DME OCT image	
		Normal	DME
Sl.No	Retinal Layers	Mean± Standard Deviation (Pixels)	Mean± Standard Deviation (Pixels)
1.	'ILM - NFL'	8.5±2.8	11.88± 9.18
2.	'NFL-GCL '	24.32±11.61	80.44 ± 40.84
3.	'GCL-IPL '	10.87 ± 5.39	38.40 ±21.46
4.	'INL-OPL '	14.85 ± 8.55	29.32± 25.13
5.	'OPL- ISOS'	63.22 ± 19.87	108.63± 32.17
6.	'ISOS - RPE'	22.70 ± 6.86	15.92 3.91

2.5. Feature Extraction

$$LBP_{p,r}(x,y) = \sum_{p=0}^{p-1} s(f(x,y) - f(x_p,y_p))2^p \quad (2)$$

The resulting decimal label value of the 8-bit word can be expressed as Equation 1. Where P is the number of neighbourhoods, R is the radius of the neighbourhood, x_p is the gray value of gray image and y_p is the gray value of its neighbourhoods. Using this LBP label for the centre pixel (x,y) of image f(x,y) is obtained.

The grey values of the 8 surrounding pixels and the thresholding functions (z) are defined as in Equation (3) as follow

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \quad (3)$$

Where s(z) is the thresholding function and the function s(z) produces 1 if the difference is above the threshold, and produces 0 otherwise.

In this work, a clockwise direction starting from the top left to down we obtained the consecutive binary codes from the cells which is the Local Binary Patterns(LBP) and feature vector of the image. In our work, the

computing LBP operator and a 3x3 neighbourhood of each pixel of an image as shown in figure 8 and using algorithm an example of an original input DME image and its LBP filtered image and histogram are shown in figure 9 as follow,

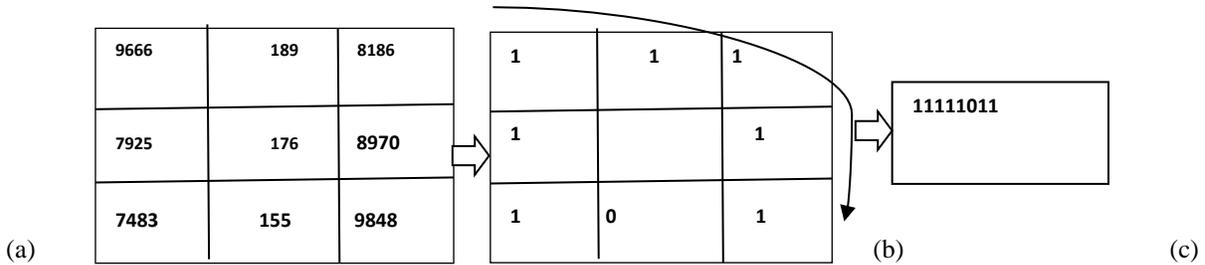


Fig. 8: LBP operator of OCT DME images (a) Extracted feature vectors of image (b) Binary thresholding 9*9 LBP operator (c) Obtained LBP Feature vector.

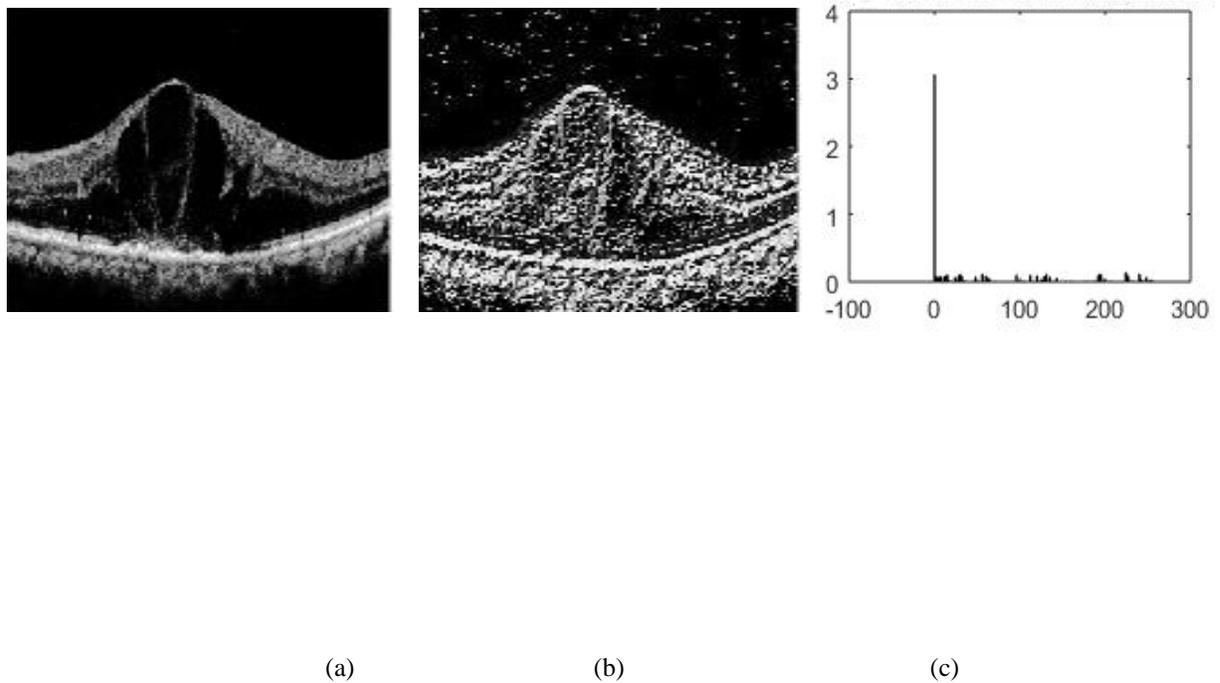


Fig 9: Example of an (a) Original DME image (b) LBP filtered image and its (c) Histogram image.

2.6. Classification

After segmentation of the retinal layers and based on the extracted features the Support Vector Machines (SVM) and Cascade Neural Network (CNN) are two classifiers used to detect and classify retinal OCT images into normal or abnormal having DME and then their performance are compared. Every classifier determines whether the applied retinal input image is normal or abnormal based on the extracted feature and the trained images.

Training-function – Training function (Default = ‘trainlm’)

The functions return a new Cascade-Forward Backpropagation network.

The trained OCT image has a nearly minimal number of input and hidden neurons as well as connections. The algorithm was successfully applied to classify normal and abnormal DME OCT images. It is slightly better than other standard fully connected neural network classifiers.

Experimental results and performance measurement

In this experiment, performance indices were carried for the detection and classification of retinal normal and DME in OCT images. In this work, the 150 OCT images datasets are acquired from Jyoti Eye Care, Puducherry. Using both classifiers 95 OCT image data sets are used for training and after training out of fifty five for testing 25 normal and 30 DME affected OCT images are used for classification and in this CNN classifier is better to correctly classify than of SVM classifier shown in Table 2.

Table 2: Classification result of Classifiers with LBP feature.

Classifiers		SVM	CNN
No. of training images		95	95
No. of test images=55	Normal	25	25
	DME	30	30
No. of images correctly classified		45	53

After classifying the retinal OCT images the performance measure are calculated by creating Confusion matrix shown in Table 3. The performance measurement parameters are calculated using the following equations (7) to (11).

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (7)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \quad (8)$$

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (9)$$

$$\text{Precision} = \frac{(TP)}{(TP+FP)} \quad (10)$$

$$\text{F-Score} = \frac{(2*TP)}{(2*TP+FP+FN)} \quad (11)$$

In this proposed work,

TP = Determine the number of abnormal DME OCT images correctly classified.

TN = Determine the number of normal OCT images correctly classified.

FP = Determine the number of normal OCT images classified as abnormal.

FN = Determine the number of abnormal DME OCT images classified as normal.

Sensitivity = the condition of the test finding the abnormal DME images among all abnormal DME OCT images

Specificity = The condition of the test finding the normal OCT images among all normal OCT images

Accuracy= Finding the fraction of the test results those are correct.

Precision=Finding the measure of a classifier's exactness result of diseases class.It predicted the total number of positive value such as DME affected diseases class. It is also called positive predictive value(ppv).

F-Score= finding the measure of a classifiers completeness..

The confusion matrix of the classification result of normal and DME affected images is as follows,

Table 3: Confusion matrix of a) LBP with SVM b) LBP with CNN

Actual class	Predicted class	
	DME	NORMAL
DME	37	3
NORMAL	7	8

(a)

Actual class	Predicted class	
	DME	NORMAL
DME	38	2
NORMAL	0	15

(b)

The performance measurement calculated results of both the classifiers of normal and DME affected OCT images are presented in Table 4 and performance Chart for DME affected diseases classification using SVM and CNN is shown in figure 12.

Table 4: Performance measurement of all the classifiers with LBP

Measure	SVM	CNN
TP	37	38
TN	8	15
FP	7	0
FN	3	2
Sensitivity	93%	95%
Specificity	53%	100%
Accuracy	82%	96%
Precision	84%	100%
F-Score	88%	97%

The chart of Performance measurement for DME affected diseases classification using SVM and CNN classifiers is as follow,

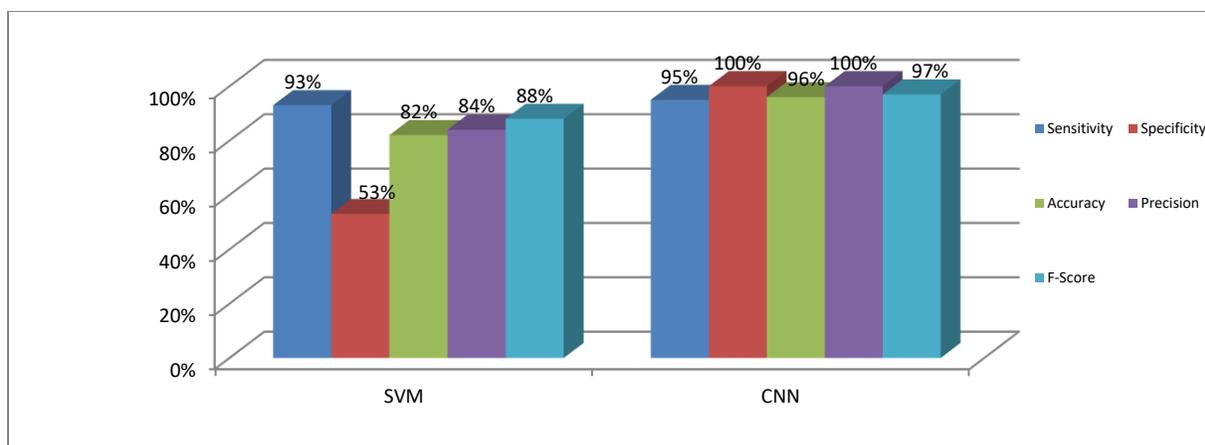


Fig 12: Chart of the performance measurement of classification results.

The Receiver Operating Characteristic (ROC) curve shows the measured accuracy performance result of classifiers of OCT images. ROC compares the true positive rate (TPR or sensitivity) in the Y axis with the false positive rate (FPR or 1-specificity). In this study, AUC (Area Under Curve) value of CNN with LBP is 96% better than of AUC value 72% of SVM with LBP. The ROC curves obtained for the LBP with SVM and CNN classifier shows in Figure 13 (a) and (b).

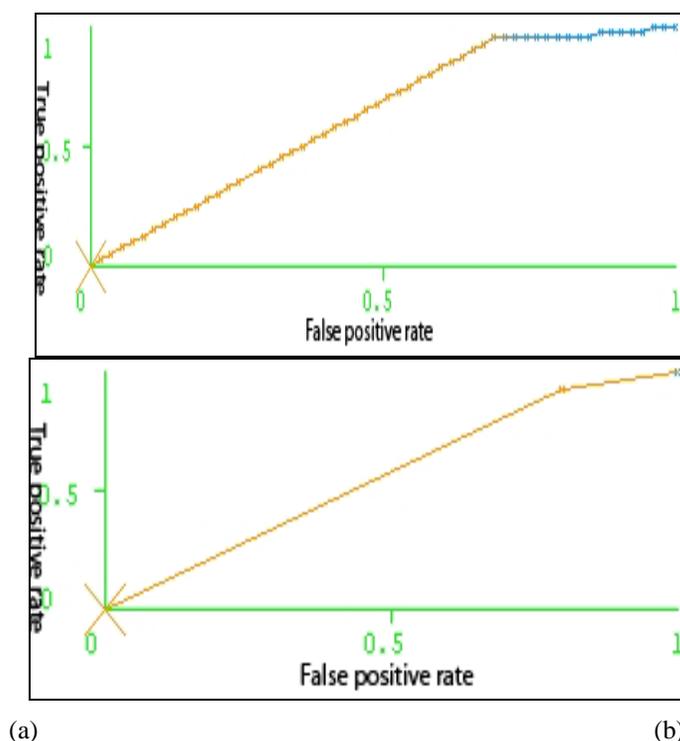


Fig 13: ROC curve of (a) LBP with SVM and (b) LBP with CNN classifiers

In this study, the CNN classifier is better to identify and classify the normal or abnormal with higher accuracy than of SVM classifier. The results showing that the trained and tested classifier CNN with LBP feature has a learns faster, higher sensitivity of 95%, specificity of 100%, and accuracy of 96%, Precision of 100% and F-Score of 97% of testing the DME affected diseases as compared to SVM classifiers with LBP feature.

CONCLUSION AND FUTURE WORK

In this work, the OCT images are segmented into different layers by two different methods and their ability to determine normal and abnormal diabetic macular edema studied. Initially the images are accurately denoised and smoothing done to the OCT images using median filtering method for detection and classification. Before extracting the features from the retinal layers for the detection of DME diseases, the six retinal layers are segmented using graph search segmentation method. Mostly DME shows as swelling of the foveal region in the macula. The detection and differences of normal or DME affected diseases images, next the average thicknesses of the six retinal layers for each of the OCT images between neighbouring layer boundaries are calculated and determined. Hence, texture local features has been extracted from the cropped layers segmented images and extracted features classified using CNN and SVM two classifiers to detect and classify normal or abnormal images. The experimental results show that, among the two classifiers the best performance of CNN with LBP was found with sensitivity of 95%, specificity of 100%, accuracy of 96%, Precision of 100% and F-Score of 97% of testing the DME affected diseases as compared to SVM classifiers with LBP feature. Further research need to be done to bring in newer deep learning classifications and based on the classifications made by detecting newer features in DME will be a future work. Thus, this algorithm can be used by ophthalmologists in early detection of Macular Edema.

ACKNOWLEDGMENT

We would like to thanks Dr. Vanaja, Jyoti Eye Care, Puducherry and Dr. Susil Kumar Pani of Raghu Eye clinic, Pondicherry for cooperating and providing OCT images required to carry out this work.

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