Research Article

Detection of Macular Edema in Acute Phase through Optical Coherence Tomography using Local Binary Pattern Feature

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Abstract: Diabetic macular edema is one of the major causes for blindness and can be detected early by using OCT imaging technique. Optical Coherence Tomography is a fundamentally novel technique of optical imaging modality. In this paper we are mainly focused to extract local features by using different methods for detection of DME followed by its classification. Used the image processing techniques of removal of the speckle noise, proper alignment followed by local feature extraction by using Local binary pattern .Then extracted features are classified using SVM classifier. In this study for testing 30 OCT images datasets in that 15 normal and 15 DME images were used for classification. We have used SVM classifier it gives the best results, likes 98, 98 and 98.77 for specificity, sensitivity and accuracy respectively. Here SVM classifier with LBP features detected the diseases with an accuracy of 98.77% our proposed method shows that the SVM classifier with LBP features gives a better improved performance.

Keywords: Diabetic Macular Edema, Local binary pattern, Optical Coherence Tomography.

Introduction

In the last decade, many tomographic imaging techniques have been developed, like Ultrasound, Magnetic Resonance Imaging (MRI) and Computer-Generated Imaging [2]. Optical Coherence Tomography technique has been developed for noninvasive cross sectional imaging in biological systems [3]. Furthermore, OCT has a determinant role in imaging due to the accuracy of micrometer resolution and millimeter penetration depth. Optical Coherence Tomography is based on the detection of infrared light waves to acquire micron scale, cross-sectional, and three dimensional (3D) image of the subsurface microstructure of biological tissues. It is analogous to B-mode ultrasound imaging, except that the echo time delay and the intensity of back-reflected or back-scattered infrared light instead of the acoustic waves, is measured. The principal operation of OCT is based on fiber optic Michelson interferometer, which performs measurements with a low coherence length light source. The “sample arm” of the interferometer illuminates the light on the tissue and collects the backscattered light and the “reference arm” of the interferometer has a reference path delay that is scanned as a function of time. Optical interference between the light from the sample and the reference arms occurs only when the optical delays correspond to within the coherence length of the light source [1]. Two basic approaches of OCT have been developed through the years, the Time Domain OCT (TD OCT) and the Fourier or Frequency Domain OCT (FD OCT). The rapid evolution of OCT reflected in

the number of publications. Based on the PubMed database for biomedical literature, the number of publications with the term “Optical Coherence Tomography” increased slowly until 200 and had a stable increase of more than 200 publications per year [4].

Optical Coherence Tomography:

The term tomography refers to the method of producing two-dimensional data derived from three-

Table1. Literature review on LBP variations, advantages and advantages from 2005 to 2017.

References	Variations	Advantages	Disadvantages
[5]	Enhanced Local BinaryPattern (**ELBP**)	Reducing noisesensitivity	Losing significant image information
[6]	CompletedLocal Ternary Pattern (**CLTP**)	Enhancing LBPPerformance	Increasing the computationalcomplexity
[7]	Robust Local BinaryPattern (**RLBP**)	Reducing noisesensitivity	Computational Complexity
[8]	Local Quinary Pattern (**LQP**)	Reducing noisesensitivity	Lose illumination-invariant.
[9]	Completed Local BinaryPattern (**CLBP**)	Enhancing LBPPerformance	Increasing the computationalcomplexity
[10]	CentralizedBinary Pattern (**CBP**)	Increasing insensitive to noise and reducing the size	Losing significant image information
[11]	Soft LocalBinary Pattern (**SLBP**)	Reducing noisesensitivity	Increasing the computational complexity andlosing invariantto monotonic grey scale
[12]	Elongated Local BinaryPattern (**ELBP**)	Addressing special image primitives (anisotropic information)	Losing rotation-invariant
[13]	Robust Local BinaryPattern (**RLBP**)	Improving robustness of the original LBP	Losing significant image information
[14]	Center- Symmetric Local BinaryPattern (**CS-LBP**)	Minimizing thelength	Losing significant image information
[15]	Level of Symmetry (**Lsym**)	Minimizing thelength	Losing significant image information

2. Literature Review

The authors have been proposed three different directional median filter implementations on FPGA. The techniques are capable of performing median filtering operations for four different directions simultaneously. These implementations are extensions to an existing cumulative histogram based median filtering technique [16]. In this paper the author was proposed a methodology for detecting macular pathology in OCT images using local binary pattern and gradient information as attributes [17]. In this paper author was used the technique local scale invariant features by computing its difference of Gaussian orientations and Hough transform for object recognition [18].

1. Proposed Methodology

The proposed methodology of DME in Acute Phase through OCT using local binary pattern feature. Following figure shows the proposed system.

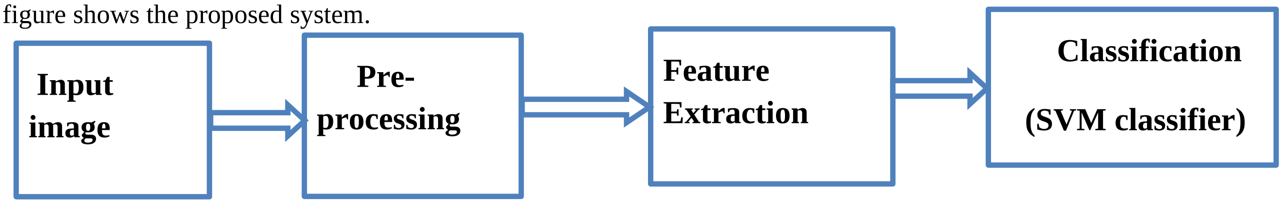


Figure 1. Block diagramme of proposed system

a. Input Image:

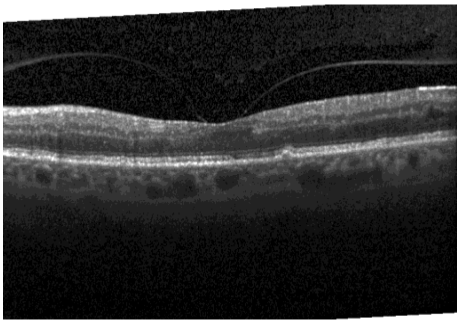


Figure 2 : Input Image

Our proposed method used 30 images, 15 are normal and 15 are macular edema images.

b. Preprocessing

After database collection preprocessing has been done.

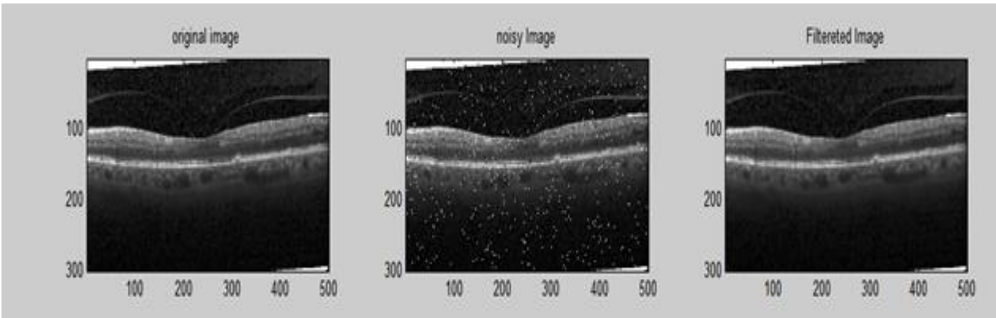


Figure 3. Preprocessing

i) Median filtering

The OCT images are corrupted by speckle noise due to high frequency sound waves, so we have to reduce the noise by de-noising them and improve the efficiency of the classification results. In this work, Median filtering is a non-linear filter method used to remove the speckle Noise from OCT images while preserving the edges and smoothening the image.

4. Feature Extraction

In this work, Local binary pattern (LBP) feature method has used. For classification a set of texture local features were extracted from the ROI portion of retinal OCT images of normal macula and diabetic macular edema.

i) Local Binary Pattern features:

Local binary patterns are an image feature descriptor technique used for recognition, modeling, detection and classification in various computer image applications. It is robust, very fast to compute and doesn't require many parameters The extracted features are used in the SVM classifier to determine the normal and abnormal image with macular diseases. The LBP operator assigned a label to every pixel of a gray level OCT image with decimal numbers in the Local Binary Patterns (LBP) codes. The label mapping to a pixel is affected by the relationship between this pixel and its eight neighbors. LBP method divides the image into several blocks. Then by using basic operator each block is converted into a matrix of size 3*3 and the pixels in each matrix have a threshold by its value of centre pixel and its eight surrounding neighbors pixels, if centre pixel >=other pixel=1, else 0, thus getting the binary number of each block. Then it is converted into decimal number to obtain the centre pixel feature vector value.

Let's take an example to understand it properly.

Let's take a pixel value from the output to find its binary pattern from its local neighborhood. So, I am taking a value '149' (present at 15th row and 19nd column) and its 8 neighborhoods pixels to form a 3 x 3 matrix.

255	253	220
220	**149**	118
128	113	118

After thresholding

1	1	1
1	**149**	0
0	0	0

Collect the thresholding values either clockwise or anti-clockwise. Here, I am collecting them clockwise from top-left. So, after collecting, the binary value will be as follows:

1	**1**	**1**	**0**	**0**	**0**	**0**	**1**

Then, convert the binary code into decimal and place it at center of matrix.

1 x 27 + 1 x 26 + 1 x 25 + 0 x 24 + 0 x 23 + 0 x 22 + 0 x 21 +1 x 20

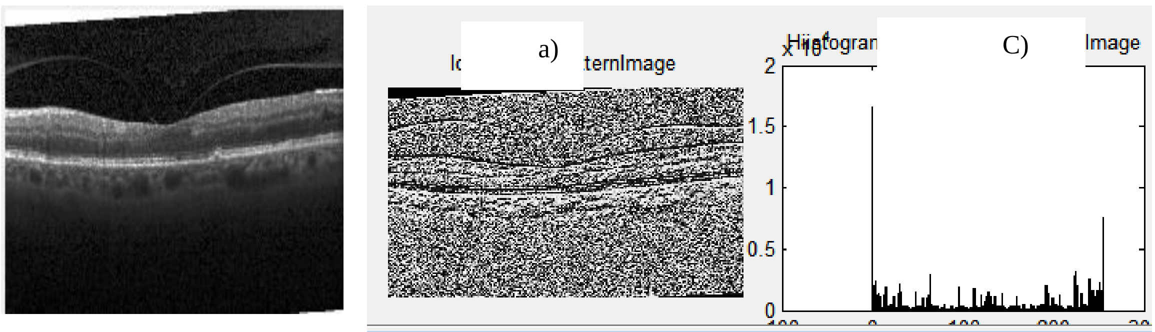
= 128 + 64 + 32 + 0 + 0 + 0 + 0 + 1

= 225

Now, the resulted matrix will look like,

255	253	220
220	**225**	118
128	113	118

LBP image and histogram image are shown in following Figures.



a b c

Figure 4. a) input image b) LBP features d) histogram of LBP features

5. Results

i) Classification

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 using SVM involves separating data into training and testing sets. Each instance in the training set contains one target value and several features. SVM is trained using 30 images, 15 are normal and 15 are macular edema images. During testing 30 images were used consisting of 15 normal and 15 DME images.

Output of the classifier is evaluated based on the following formulas,

Sensitivity: 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.

$Sensitivity = TP / (TP + FN) \, X \, 1\,00$ **-------- (1)**

Specificity: 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.

$Specificity = TN/(FP + TN) \, X \, 100$ **------- (2)**

Accuracy: Measure of correct predictions of presence or absence of the abnormality in the image out of total number of images.

$Accuracy = TP + TN/ \, (TP + FN + FP + TN) \, X \, 100$ **---- (3)**

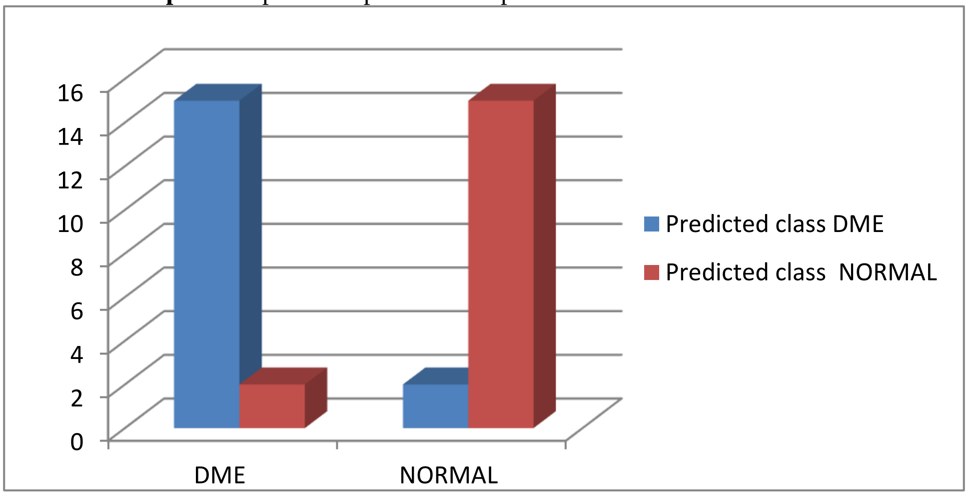
Using these formulas the following performance measure are calculated.

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

Table2. Confusion matrix

	Predicted class	
	DME	**NORMAL**
DME	**15**	**02**
NORMAL	**02**	**15**

Graph1. Graphical Representation predicted class of DME and Normal

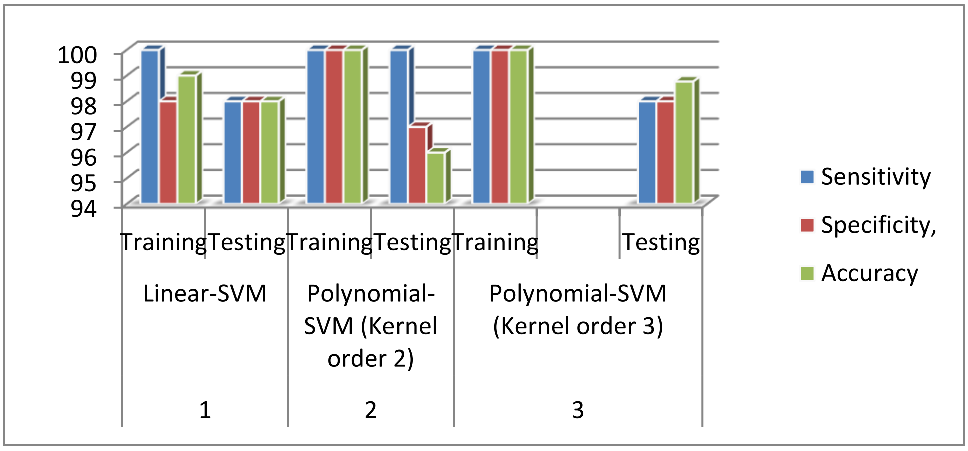


Following table 3 shows the SVM classifier performance measures of our proposed system.

Table 3. SVM classifier performance

Sr.No.	**Classifier**	**Dataset**	**Sensitivity**	**Specificity,**	**Accuracy**

1	Linear-SVM	Training	100	98	99
		Testing	98	98	98
2	Polynomial-SVM (Kernel order 2)	Training	100	100	100
		Testing	100	97	96
3	Polynomial-SVM (Kernel order 3)	Training	100	100	100
		Testing	98	98	98.77



Graph 2. SVM classifier performance

Performance measures of classification shows that SVM accuracy is **98.77%**

6. Conclusion

In this paper we present automated methods which are mainly focused on the detection and classification of normal and abnormal OCT images in diabetes patients. In this proposed technique, the test and patient images are filtered with median filter; LBP features of images are extracted. Then SVM classifier is used to detect and classify the extracted features of OCT images either as normal or abnormal having different types of DME. The experimental results show that Local Binary pattern with SVM classifier gives better performance and Performance measures of classification shows that SVM classifier is 98, 98 and 98.77 for specificity, sensitivity and accuracy respectively.

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