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Detection of Hard Exudates in Color Fundus Images Based On ELM Classifier

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Abstract- Diabetic Retinopathy is an eye disease caused due to diabetes complication. It leads to vision loss if not diagnosed at early stage. It can be assessed by detecting the hard exudates present in the color fundus images. The proposed methodology has two stages such as detection of hard exudates and classification of severity stages of diabetic retinopathy. A feature extraction technique is used to capture the global features like intensity, color and texture features. It is very useful to categorize the normal and abnormal images. In this, the detection of hard exudates is done by using ELM classifier. Classification of disease severity stages is assessed by using regional property of the hard exudates in the retinal image. The proposed detection performance has a sensitivity of 99% with specificity between 85% and 96%.

Indexed Terms- Diabetic Retinopathy, Hard exudates, Discrete wavelet transform, Extreme Learning Machine Classifier.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a general cause of blindness and vision effects. It is a very severe and widely spread eye disease. The automatic detection of hard exudates is one of the essential processes in a complete analysis of retinal disease. Exudates are the most common prevailing lesion in the early stages of diabetic retinopathy. They appear as bright structures with well-defined edges and uneven shapes [2]. A number of studies have been carried out to automatically detect hard exudates based on their size, shape, texture, etc. The color fundus images are used to extract features and detect HEs in retina as well as to establish their locations, sizes, and the disease severity level. [6]. Early diagnosis through regular screening and treatment has been shown to prevent visual loss. Hard exudates and hemorrhages are visual, and they are the most abnormal indicators of diabetic retinopathy. The HEs are a very important pathological lesion used to improve the separation between exudates and non-exudates region. If the exudates are detected during retinal examination it takes immediate treatment ranging from blood pressure control to laser surgery.

II. METHODOLOGY

In the proposed work, Extreme Learning Machine (ELM) classifier algorithm is introduced for detection of HEs. The proposed system combines image analysis and pattern recognition with machine learning techniques to examine diabetic retinal images. ELM classifier has fast speed and gives the best performance for the detection of hard exudates. As a result, two performance characteristics such as sensitivity and specificity are calculated to evaluate the proposed work.

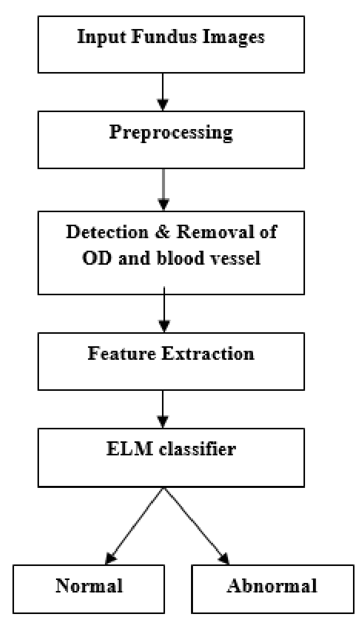


Fig 2.1 Flow Diagram of the Proposed System

Fig 2.1 shows the processing steps to detect hard exudates in the input fundus image. This is also one of the best techniques for the automatic detection of hard exudates.

A. Input Image

The first stage is acquiring an input image. Input images are downloaded from publically available database set "DRIVE''.

B. Preprocessing

The input images have to be pre-processed to resolve the problem of uneven illumination, non-sufficient contrast between exudates & image background pixels and presence of noise in input image. At First, green channel of the input image is separated because it contains the almost information on the brightness and structure of exudates compared to the red and blue channels. Color normalization and contrast enhancement modules are done before starting the detection of HEs module [11]. Blood Vessels are removed by using volterra filter. The volterra series model is the most widely used in nonlinear adaptive filtering techniques. Then finally, adaptive histogram equalization is applied on the filtered image to improve the contrast of the image.

C. Removal of Optic Disc

OD can be appeared as bright yellowish or white region and also varies from person to person. The maximum variance method can be used for the detection of optic disk.

D. Feature Extraction

Feature extraction is the process of selecting a subset of relevant features for use in model construction The Discrete Wavelet Transform (DWT) is used to extract intensity feature of hard exudates. In DWT, the image is transformed in to four sub bands. In this extract intensity based features such as intensity, size, texture, mean and variance are calculated.

E. Extreme Learning Machine Classifier

ELM classifier is a single hidden layer neural network based supervised classifier. It requires setting of parameter. Finally, it will be produced a unique solution for a set of randomly assigned weights. Given a training set,N= $\{(x_i,t_i)|x_i$ £ R^n, t_i, £ R^m , i=1, ... , N},g is the activation function , and L is the number of hidden nodes.

Assign randomly input weight vectors or centers a_i and hidden node bias or impact fact, b_i i= 1 , ….. , L.

Calculate the hidden layer output matrix H.

Calculate the output weight β:

$$\beta = (H^{+})T \quad (1)$$

H+ is the Moore-Penrose generalized inverse of hidden layer output matrix H.

$$H+ = (H^{T}H)^{-1}H^{T} \quad (2)$$

Here H is the hidden layer output matrix.

Here the output weight maximizes the two different classes in the ELM feature space. It reduces the processing time to train the network.

F. Performance Evaluation

There are two performance characteristics calculated as follows:

i) Sensitivity

The sensitivity shows the proportion of actual positives which are correctly identified [6].

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

ii) Specificity

The specificity shows the proportion of actual negatives which are correctly identified [6].

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4)$$

Here,

TP - correct classification of abnormal

FP - incorrect classification of abnormal

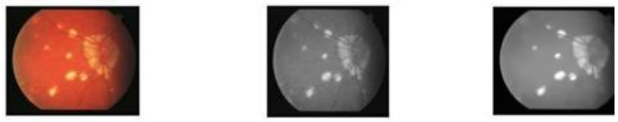
TN - correct classification of normal

FN - incorrect classification of normal

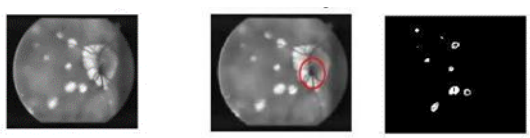
III. RESULT AND DISCUSSION

An experimental result of proposed module is presented in this part. There are two cases for the detection of hard exudates, namely normal and abnormal cases in color fundus images.

(A) Abnormal Image



(a) Input Image (b) Green Channel (c)Filtered Image



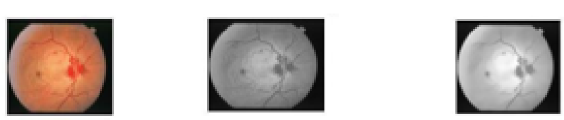
(d) Contrast Image (e) Holes closing image (f) Hard Exudates detection

Fig 3.1 Hard Exudates Detection using ELM Classifier in Abnormal Image

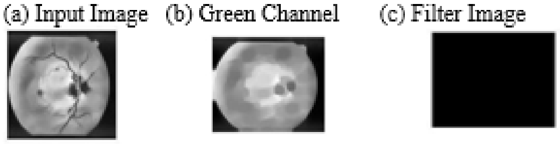
Fig 3.1 (a) shows the input image and green channel of the image is shown in Fig 3.1 (b). The blood vessels and noise in the images are removed and shown in Fig 3.1 (c). Fig 3.1(d) shows the contrast enhancement of green channel image. Fig 3.1(e) represents morphological operations that are used to fill the holes in an image such as dilation and erosion. Then the ELM classifier can be used for the detection of hard exudates. It defines the condition of input images such as normal or abnormal condition.

(B) Normal Image

This is the second case for the detection of hard exudates. Generally the normal case has no disease and clear vision. In normal case the color fundus image has no exudates and effects.



(a) Input Image (b) Green Channel (c) Filter Image



(d) Contrast Image (e) Holes closing image f) Hard Exudates detection

Fig 3.3 Hard Exudates Detection using ELM Classifier in Normal Image

(C) Performance Evaluation

The ELM classifier gives better performance for sensitivity and specificity.

Table 3.1 Performance Evaluation of the Abnormal Images

Input Image	TP	FN	FP	FN
1	93.46	6.53	93.46	6.53
2	97.36	2.63	97.36	2.63
3	98.18	1.81	98.18	1.81
4	85.12	14.81	85.18	14.8

Input Image	Sensitivity %	Specificity %
1	94	93
2	98	97
3	99	98
4	86	85

Table 3.1 shows the performance measures for different abnormal input images. Here it has better sensitivity and specificity.

CONCLUSION

Thus the detection of HEs was done by using ELM classifier. By adopting the ELM classifier in the proposed work, high Sensitivity and Specificity & low training time are achieved. ELM classifier is practicable choice model for large scale computing and artificial intelligence. The extreme learning machine has a number of advantages such as ease of use, faster learning speed, higher generalization performance, suitable for many nonlinear activation function and kernel functions. The ELM classification has been successfully used in various applications.

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