Middle-East Journal of Scientific Research 24 (S1): 450-457, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.24.S1.75

Extraction of Blood Vessels for Retinal Image Analysis

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Abstract: In this paper, an automated screening system to diagnose the retinal images affected by diabetic retinopathy is recommended. The proposed system consists of 3 stages; the pre-processing, which was done to make the image reliable for extracting features. In the second stage, features like area of blood vessels and texture features were extracted from the retinal images and classification – the last stage was done using the ELM classifier. The above steps were implemented and evaluated using images available in DIARETDB0 and DRIVE database. Our proposed method shows a high accuracy of 95% with 96%sensitivity.

Key words: Diabetic Retinopathy · Extreme Learning Machine · Blood Vessels · Mathematical Morphology

INTRODUCTION

Diabetes is an epidemic disease in adult population thoughout the world due to lifestyle and socioeconomic changes. In the current scenario, the developing countries are prone to greater risk of this disease. In addition, diabetes over ten years old, have an extremely high risk of affected by diabetic retinopathy (DR). An improved care of diabetes leads to longer life expectancy which in turn increases the prevalence of DR. DR involves the abnormal growth of blood vessels in the retina and based on the presence of various clinical abnormalities like exudates, micro aneurysms, blood vessels and so on the severity is analyzed. Detection and qualitative measurement of variations in the retinal images can help in detecting if abnormality is present or not.

An algorithm was proposed in [1] for temporal and/or multimodal registration of retinal images based on point correspondence which could be merged with some detection algorithm to improve the diagnosis of disease with morphological filter and cross curvature method being used for segmentation of blood vessels. A fully automated approach for robust detection and classification of changes in longitudinal time series of retinal images were developed by the authors in [2]. To exploit retina – specific information, they proposed an iterative robust homomorphism surface fitting algorithm for analyzing the structural changes of the vasculature and does not analyze vascular changes.

Palomera-Pérez *et al*. [3] used feature extraction based region growing algorithm for the segmentation of blood vessels. The domain partitioning based parallelism was used to group the vessels while Niemeyer *et al* [4] proposed an algorithm for classification of pixels in retinal image using simple feature vector. Hoover *et al* [5] used matched filter response and threshold probing process to detect the retinal blood vessels.

For detecting the blood vessels of retinal images Mire and Mahloojifar [6] applied curve let transform and morphological operators. Zhang et.al., [7] proposed a modified matched filter with double sided thresholding for retinal vessel extraction which responds to online edge by applying local double - sided thresholding for segmentation, but results in higher true positive rate and lesser false detection. Simple morphological operations were used to detect features such as blood vessel and exudates [8].

A supervised classification proposed by Soars *et al* uses Gabor wavelets and Bayesian classifier for detecting blood vessel. Aquino et.al., [9] proposed a method for blood vessel classification using neural networks based on pixels by considering the gray level and moment invariant features and got an accuracy of 94%. Ricci et.al., [10] developed a framework for diagnosing retinal image using retinal vessel segmentation based on line operators and used support vector machine (SVM) for supervised classification.

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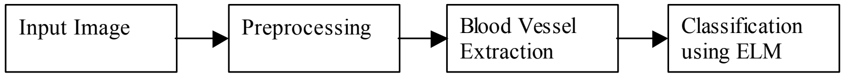


Fig. 1: Architectural Block Diagram

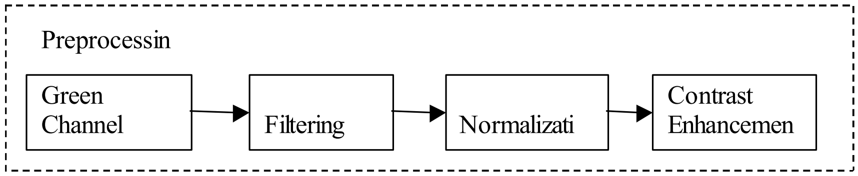


Fig. 2: Pre-processing Steps

The proposed method achieves improved detection in abnormal retinal images by exploring a computationally simpler and identifies the individual features of images effectively. For our method we have used the images from the publicly available database, DRIVE and DIARETDB1 and have used Extreme Learning Machine for image classification. Our proposed method has achieved a sensitivity of 96% and specificity of 95%.

The rest of the paper is organized as follows: In section II the details of the proposed algorithm discussed; Section III deals with the Extreme Learning Machine; Section IV analyzes the performance results of our approach; Section V concludes by summarizing our contributions and describing potential future work.

Autotmatic Detection of Dr Using Extreme Learning Machine: The proposed system consists of three stages, preprocessing, blood vessel detection and classification of retinal images as normal and abnormal. Figure 1 shows the block diagram of proposed work. The pre-processing step minimizes the imperfections and helps in extracting the blood vessels. In the last step the ELM classifier is used to classify the retinal images as normal and abnormal images.

Pre-Processing: In order to reduce the imperfections and generate images suitable for extracting the features, a four step pre-processing procedure is applied in this work and they are described in Figure 2.

Green Channel Extraction: To enhance the contrast of the retinal images, information in red and blue components of the image are discarded as only the green band displays the best vessels/background contrast and the greatest contrast between the optic disc and the retinal tissue. The subsequent feature extraction process will be made simpler if a single channel image is used. Hence the green pixel values are extracted using equation (1).

$$g = \frac{G}{(R+G+B)} \tag{1}$$

Here g is the green channel and R, G and B denotes Red, Green and Blue component of the image respectively. The green channel of the original RGB image is shown in Figure 3b

Filtering: Retinal images may be noisy, low contrast with non-uniform illumination and it is necessary to deepen the contrast of these images for subsequent image analysis step. Median filtering is a nonlinear method used to remove noise from images.

$$\hat{f}(x,y) = \underset{(x,y)\in s_{xy}}{median} \{g(s,t)\} \tag{2}$$

where s, t represents the pixel value present in the moving window and x, y represents the pixels present in the original image.

a. Original image b. Green Channel Extraction c. Filtered Image

e. Normalized Image f. Contrast Enhancement

Fig. 3: Illustration of steps of pre-processing

Normalization: Contrast stretching normalization attempts to improve an image by stretching the range of intensity values it contains to make full use of possible values and it is restricted to a linear mapping of input to output values. Filtered image was normalized to increase its contrast using the equation (3).

$$\text{Normalization} = (I - Min)\frac{(NewMax - newMin)}{(Max - Min)} + newMin \tag{3}$$

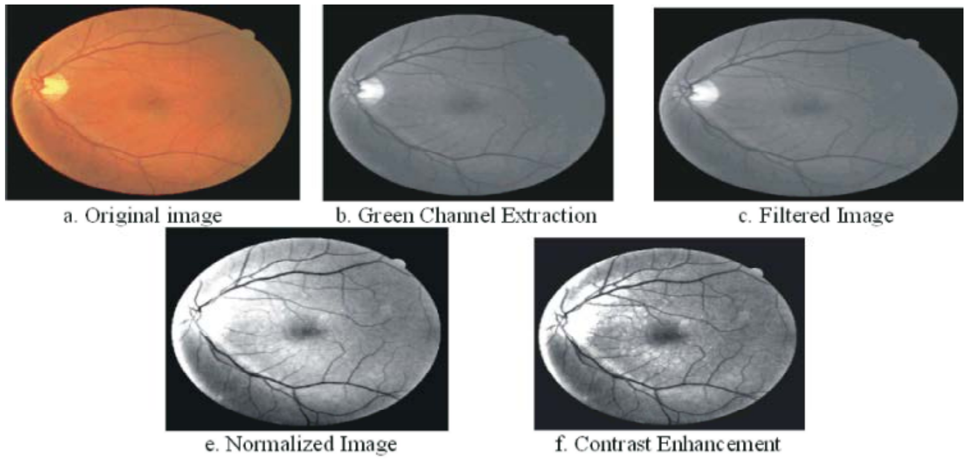


Fig. 3: Illustration of steps of pre-processing

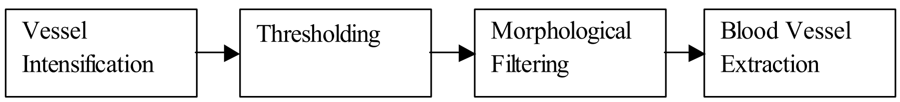


Fig. 4: Steps for blood vessel extraction

Contrast Enhancement: To the resultant image, Contrast Limited Adaptive Histogram Equalization (CLAHE) [11] was applied by limiting the maximum slope in the transformation function to enhance the contrast adaptively across the image. The CLAHE DR image is median filtered to smoothen the background inhomogenities to reduce impulse noise and the ability to preserve edge information of resultant image and its output is shown in figure 3f.

Blood Vessel Detection: For effective treatment of DR patient, the challenging task is to detect features such as swelling, leaking of fluid in blood vessels and growth of abnormal new blood vessels automatically. The presence of noise, the size of vessel width and the presence of some pathological lesions makes the task more difficult.

In this paper, algorithms based on mathematical morphology are developed for retinal vessel segmentation. Figure 4 shows the process involved in extracting blood vessels.

Vessel Intensification: In the proposed approach, the vessels in the retinal image are strengthened using top-hat transform and it is carried out by estimating the local background by a morphology opening operation, which is subtracted from the original image resulting in enhanced vessels [12].

$$t_h(f) = (f \circ b) - f \tag{4}$$

where $t_h(f)$ represents top hat transformation, (°) is the opening operation, b is the structuring element and f is the filtered image.

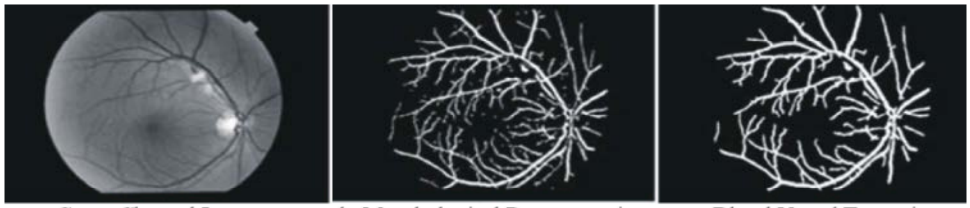
Thresholding and Filtering: To remove the unnecessary details, thresholding (13) technique is applied that converts the image into binary image. Pixel based thresholding is used to extract an object from its background by assigning an value T value for each pixel such that each pixel is either classified as an object point or a background point. T is the threshold and v is the pixel

$$\text{img(imp)} = \begin{cases} 0 \; if \; v < T \\ 1 \; if \; v \geq T \end{cases} \tag{5}$$

Value. Then the smallest details are removed using morphological filters [22].

Blood Vessel Extraction: Blood vessels can be recognized by determining the area, perimeter and circularity of the blood vessel. The area is determined by the number of pixels present and the perimeter is estimated by counting the number of pixels present on the periphery of the vessel [14]. Circularity of the shape of the region is defined by the following equation:

$$Circularity = (4 * 3.14)\frac{Area}{(Perimeter)^2} \tag{6}$$



a. Green Channel Image b. Morphological Reconstruction c. Blood Vessel Extraction

Fig. 5: Illustation of blood vessel detection

Vessel size may decrease when moving away from the optic disk, the width of a retina vessel may lie within the range of 2–10 pixels. Therefore, the details whose circularity value is ≥ 0.2 are not considered as blood vessels and it is removed. The output of the image is shown in Figure 5c.

Texture Analysis: Texture of an image helps to segment images into regions of interest and classify those regions. It can also define characteristic of regions [15] and gives information about the arrangement of surface pixels and their relationship with the surrounding pixels. The texture features [16] considered for this work are mean, standard deviation and third momentum.

Mean measures the average intensity; standard deviation represents the average contrast while third momentum gives the measure of scenes of a histogram. Entropy gives the randomness of grey-level distribution while energy corresponds to the mean squared value of the image typically measured with respect to the global mean value. Contrast of an image returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$\text{Mean } \mu = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} i P_{i,j} \tag{7}$$

$$\text{Standard Deviation } \sigma = \sqrt{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{i,j} (1-\mu)^2} \tag{8}$$

$$\text{Third Momentum } m_g = \sum_{i=0}^{N-1} (zi - m)^3 p(zi) \tag{9}$$

$$Entropy = -\sum_i \sum_j P[i,j] \log P[i,j] \tag{10}$$

$$Energy = \sum_i \sum_j P^2[i,j] \tag{11}$$

$$Contrast = \sum_i \sum_j P(i-j)^2 P[i,j] \tag{12}$$

where $P_{i,j}$ represents the pixel value at location i, N denotes the number of gray levels, $p(z_i)$ represents the corresponding histogram for i=0,1,2,…,N-1, Z represents random variable denoting a gray level and m_g where g denotes the integer power exponent that defines the moment order.

Implementation of ELM for DR Analysis: The extreme learning machine (ELM), a single hidden layer neural network is an extremely fast learning algorithm with good generalization performance and requires setting of one parameter and produces a unique solution for a set of randomly assigned weights. The details about the ELM algorithm are given in Appendix I.

MATERIALS AND METHODS

The proposed methodology was tested on the images of 2 publicly available databases, the DRIVE (Digital Retinal Images for Vessel Extraction) and DIARETDB1. The DRIVE database [17] contains 40 colour images of the retina with 565*584 pixels. The 40 images were divided into 20 training images and 20 testing images by the authors of database. The DAIRETDB1 [18] consists of 89 images. All the 109 images were used for evaluation. Out of 109 images, 87 images were taken for training and 22 for testing. The images were classified based on the values of the extracted features.

The value of area of blood vessels and texture features were given as input to single layer feed forward neural network for classification into different retinopathy stages into normal and abnormal retinal images. The activation function like sine, Gaussian, sigmoid etc., can be chosen for hidden neuron layer and linear activation functions for the output neurons. The size, count and distribution of blood vessels and texture features help in classifying the image as normal or abnormal retinal image.

Table 3: Comparison of training and testing time

Parameters	Neural Networks	SVM	ELM
Training Time in secs	8.74	0.305	0.105
Testing Time insecs	0.092	0.0635	0.0424

Table 4: Classification Accuracy

Classifiers	# Training Images	#Testing Images	#Correctly Classified images	Correctly Classified images%
Back Propagation Neural Network	87	22	16	72.7
Support Vector Machine	87	22	20	90.9
Extreme Learning Machine	87	22	21	95.4

Simulation Results

Performance Measures: In this section, the classification performance of the classifier is analyzed. There exist numerous performance measures in the literature of image classification domain. The performance criterion considered for analyzing the proposed method are sensitivity, specificity, accuracy and area under the curve in receiver operating characteristic (ROC). The following table shows the features considered for the analysis of retinal image.

Training & Testing Time: The performance of the ELM network depends on the number of neurons in the hidden layer and the activation function to be used [19]. The features which we have extracted along with sigmoid activation function are fed as input to the ELM classifier and it classified the retinal images based on the disease severity with an accuracy of 95%.

Table 3 shows the comparison of training time and testing time taken for classification.

The above table shows the training time for ELM is less when compared with other classifiers.

The classification accuracy obtaine using ELM classifier is high when compared with other classifiers.

Classification Accuracy: The indexes used to quantitatively measure the performance of our automatic classification method include - Detection Accuracy, Misclassification Rate, Sensitivity and Specificity. The accuracy is estimated by the ratio of the total number of correctly classified points.

$$Misclassification\,Rate = \frac{Number\ of\ wrongly\ classified\ images}{Total\ Number\ of\ images} * 100 \tag{13}$$

The misclassification rate for BPNN, SVM and ELM is 0.18, 0.22 and 0.24 respectively.

Sensitivity & Specificity: Sensitivity means the percentage of abnormal fund uses classified as abnormal by the procedure and specificity gives the percentage of normal fund uses classified as normal by the procedure. The higher the sensitivity and specificity values, the better the procedure.

Sensitivity and specificity values can be calculated as follows

$$Sensitivity = T\frac{P}{T}P + FN \tag{14}$$

$$Specificity = T\frac{N}{T}N + FP \tag{15}$$

$$Auracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

where TP, TN, FP and FN denotes mean true positive, true negative, false positive and false negative, respectively. A screened fundus is considered as a true positive if the fundus is really abnormal and is classified as abnormal by the algorithm and a true negative refers to negative pixels correctly labelled as negative [20]. A false positive means that the fundus is actually normal, but is classified as abnormal whereas false negative indicates the procedure which classified the normal as abnormal.

Receiver Operating Characteristics (ROC) Curve: A ROC curve is a plot of true positive rates and false positive fractions by varying the threshold on the probability map. The closer a curve approaches the top left corner, the better the performance of the system. The area under the curve (AUC) which is 1 for a perfect system is a single measure to quantify the system.

While using ELM, the area under the ROC curve is 0.96. The properties of ROC curve area [21, 22] we can conclude that classification obtained using ELM is good. Figure 6 shows the ROC curve obtained while using ELM. The ELM classifier works well for huge data set and also the classification accuracy is high than the existing techniques like BPNN and SVM.

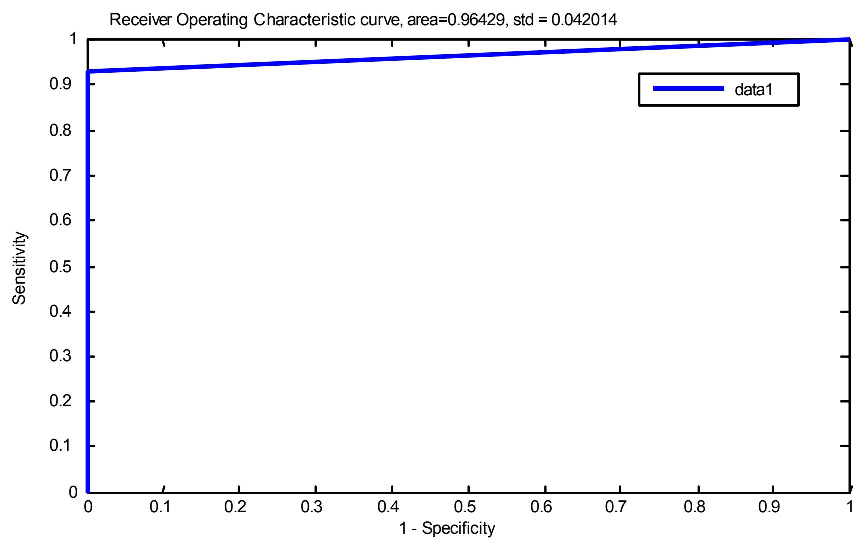


Fig. 6: ROC Curve

CONCLUSION

The proposed work helps the ophthalmologists to detect the diabetic retinopathy at early stage thereby helping the patients to undergo treatment without any delay. In our method, after applying pre-processing the concept of morphological image processing is applied to the enhanced image for feature extraction. Along with the area of blood vessels, the texture features were identified and used for blood vessel detection. These features were fed as input to the ELM classifier for classifying the retinal images. The results show that by using our procedure we could get high classification accuracy when compared with the other techniques and also the sensitivity is 93%. As future work, we can use other features like area of exudates and micro aneurysms along with the advanced classification techniques can be used for producing reduced complexity.

Annexure 1:

Extreme Learning Machine (ELM): Extreme learning machine (ELM) is based on empirical risk minimization theory and it is widely applied in learning of Single Layer Feed forward Neural network (SLFN). The working principle of ELM can be better understood from the diagram given below.

As shown in the Figure 10, the number of nodes in input and output layers depends on the problem and for hidden layer, it is calculated adaptively. The weights and biases for the input and hidden layer [23] are assigned randomly.

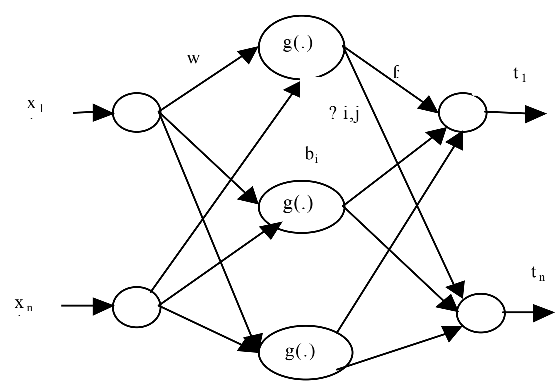


Fig. 7: The Architecture design of ELM

The output layer weights are obtained by using the Moore-Penrose (MP) generalized inverse i.e., finding a least-squares solution for the linear system using $\beta\|H\beta - T\|$ where, H is called the hidden layer output matrix of the neural network, β is the weight vector connecting the hidden neuron and the output neurons and T is the target vector. For all the layers, non-differentiable or even discontinuous functions are used as activation functions. With these settings of ELM, SLFNs can be simply considered as a linear system for mapping the input with the output that provides good generalization performance. Further, this kind of learning is faster, tends to reach small training error and weights. The steps of implementing the ELM are briefly given below:

Given the training sets $\{x_i, y_i\}, i = 1, \cdots, N,$ the activation function $g(x)$ and the number of hidden nodes $\tilde{N}$,

- 1. Assign randomly input weight w_1 and bias b_1 for $i = 1, \ldots, N$ and define hidden layer node number $\tilde{N}$;

- 2. Calculate the hidden layer output matrix H.
- 3. Calculate the output weight β: $\tilde{\beta} = H^{-1}T$.

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