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Multi Criterial Analysis for Diabetic Retinopathy

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Abstract: In this study, an automated screening system to diagnose the severity of diabetic retinopathy is recommended. The proposed system consists of 3 stages; the preprocessing being the first one is done to make it reliable for extracting features. In the second stage, features like area of blood vessels, exudates, micro aneurysms and texture features are extracted from the retinal images and classification, the last stage is done using the ELM classifier. The above procedures were implemented and evaluated using images available in DIARETDB1 and DRIVE database. Our proposed method shows a high accuracy of 95% and overcomes the slow training speed when compared with other classifiers.

Key words: Diabetic retinopathy, extreme learning machine, exudates, mathematical morphology, microaneurysms

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. With increase in diabetes, there is observed increase in Diabetic Retinopathy (DR). Currently, it is estimated that atleast 171 million people worldwide have diabetes; this figure is likely to be more than double by the year 2030-366 million. 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. World heath organization has estimated that DR is responsible for 4.8% of the 37 million cases of blindness throughout the world. DR involves the abnormal growth of blood vessels in the retina. Complications can lead to serious vision problems: vitreous hemorrhage, retinal detachment and finally blindness.

DR is a progressive disease classified according to the presence of various clinical abnormalities like exudates, microaneurysms, blood vessels and so on. Exudates appear as bright patterns in retinal images. They are manifested as random whitish/yellowish patches of varying sizes, shapes and location. Microaneurysms (MA) appear as small, round shaped, red dots on the retinal images. In general, DR is classified as Proliferative and non proliferative DR in which the former induces vision loss due to formation of new vessels in retina and the later is characterized by the presence of MA's, cotton wool spots, soft exudates and small haemorrhages. Need for measurement of those features arises, as they are not easily observable with human eye. A much finer quantitative analysis of the retina is also needed. Therefore a greater effort is required to develop computer based program for detection of the more difficult aspects of retinopathy.

An algorithm was proposed in Zana and Klein (1999) for temporal and/or multimodal registration of retinal images based on point correspondence. They have tested the algorithm on fluorescent images as well as green images of the retina. This registration method could be merged with some detection algorithm to improve the diagnosis of disease. Walter *et.al*. (2002) found the presence of exudates using high gray level variation and contours are determined by morphological reconstruction techniques. This approach was difficult to distinguish hard and soft exudates and distribution of detected exudates in order to detect macular edema. Li and Chutatape (2004) proposed a method to detect exudates by the combined region growing. A fundus coordinate system was established to provide a better description of the features of the retinal image. Principal component analysis was applied to locate the optic disk.

A fully automated approach for robust detection and classification of changes in longitudinal time series of colour fundus images were developed by the authors Narasimha (2006). To exploit retina specific information, they proposed an iterative robust homomorphic surface fitting algorithm that combines the advantages of homomorphic filtering and surface fitting. Their work

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mainly focused on analyzing the structural changes of the vasculature and does not analyze vascular changes. Fawcett (2006) proposed a method for identification of other features in retinal images by improving the ability to distinguish microaneurysms and other dots using image contrast normalization.

Ricci and Perfetti, (2007) developed a framework for diagnosing retinal image using retinal vessel segmentation based on line operators. They have employed two orthogonal line detectors along with the gray level of the target pixel to construct a feature vector for supervised classification using Support Vector Machine (SVM). Noise present in the segmented image is eliminated. Yun *et al.* (2008) constructed a sorting system based on the idea of hierarchical grading approach with multilevel knowledge representation. This sorting system possesses multiple layers depending on the specific application of interest. Quellect *et.al.* (2008) introduced a new template matching algorithm in wavelet domain to detect MA, but sensitive to quality variation between images (Yen and Leong, 2008).

Ram *et al.* (2011) proposed a method where the strategy is to get a set of candidate MAs using a simple threshold from a preprocessed image and then culling the clutter with successive rejection based strategy. Candidate selection due to the variability found across datasets can be done easily using advanced machine learning approaches. Agurto *et al.* (2014) proposed an automatic system to detect exudates in macula, using optimal thresholding of instantaneous amplitude components that are extracted from multiple frequency scales to generate candidate region, color, shape and texture features used for classification. Classification is performed using partial least squares which is recommended for soft models those describing many sets of observations containing much correlated error.

Miri and Mahloojifar (2011) applied curvelet transform and morphological operators for detecting the blood vessels of retinal images using Otsu's thresholding method that was not able to recognize some thin and small blood vessels for evaluation. Zhang *et al.* (2009) proposed a modified matched filter with double sided thresholding for retinal vessel extraction. Although, it responds to nonline edge by applying local double-sided thresholding to segment the retinal image, 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 (2010).

Quellec *et al.* (2008) authors used three stage algorithm to automatically detect and grade the severity of DR. DR classification specificity was improved while retraining the lesion classifiers for every new test set of images. Osareh *et al.* (2002) developed an automated system to detect exudate pathologies by applying fuzzy c means clustering method over the preprocessed retinal image. The segmented regions were classified using neural network based on scaled conjugate gradient learning method. Research by Osareh *et al.* (2009) used genetic algorithm for ranking the features and multilayer neural network trained using backpropagation learning method was used for identification of exudates and established the spatial relationship between the detected exudates and the fovea.

Marin *et al.* (2011) 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% when tested over the DRIVE database. Schaefer (2007) applied sliding window technique for exudates detection and used backpropagation neural network for classification. Principal component analysis and histogram specification were used to reduce training times and complexity. Sopharak *et al.* (2011), a pixel by pixel classification was proposed to check whether the region is a exudates or not but it requires a high computational power for training and classification processes.

Lazar and Hajdu (2013) proposed a methodology to detect MA by analyzing the directional cross section profiles in the local maxima of the preprocessed image. After feature selection process, Naïve Bayes (NB) classifier was used. Also other classification methods like SVM with different kernel functions and k-nearest neighbor were also used and found that NB gave a slightly better result. Optic disc detection was included and MA regions detected within this region were eliminated. Sopharak *et al.* (2011) developed the MA detection and grading system by adjusting morphological operators and it was successful on very poor quality images. Their proposed method can be combined with exudates detection system B. Antal, A. Hajdu proposed an ensemble based framework to improve MA detection. They proposed a combination of preprocessing methods and candidate extractors for MA detection. Further improvements can be done by adding more preprocessing methods and candidate extractors.

In contrast to the above method the proposed method measures the important changes. We explore a computationally simpler and identify 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 based on the severity of disease. Our proposed method has achieved a sensitivity of 96% and specificity of 95%.

Diabetic retinopathy: Complications and challenges eyes are the organ associated with vision that is protected by the eyelids. It is nearly spherical in shape with average approximately 25 mm diameter. Light entering the eye through the pupil is focused on the retina. The retina is made up from special cells called rods and cones which act as receptors of our eyes. The optic disk is brighter than any part of the retina and is normally circular in shape. It is also the entry and exit point for nerves entering and leaving the retina to and from brain in Fig. 1 shows the schematic of internal structure of eye.

Diabetes affects the eyes, among other parts of the body. Shortly after being diagnosed with diabetes, we may not detect any changes in our vision. It may take time for our vision to be affected. However, harmful changes in our retina can take place without affecting our vision. The term retinopathy covers various disorders of the retina that bring damage to the tiny blood vessels and lead to vision threatening complications.

Figure 2 shows the normal and diabetic affected retina. Specs of dark spots appear in the retina due to the bleeding of blood vessels. When this becomes severe, the vision could get blocked completely. Symptoms may only become noticeable once the disease advances. Hence people with diabetic retinopathy can suffer significant vision loss. Also, the patients tend to be in the most economically productive age group and if sight stabilisation or restoration is not achieved, then the loss is substantial not only to the individual but also the society. Therefore, early detection through regular screening is important. Based on current estimates, a minimum of 3 million eyes will need to be evaluated each day by 2030. In spiteof 54% increase in the diabetes population there will be less than a 2% growth in the number of ophthalmologists by 2030. So there is a limited availability of a trained workforce at all levels limits service quality and reach. Hence there is an immediate requirement to develop effective diagnosis method at the early stage. With early detection and treatment by an ophthalmologist, the risk of severe vision loss can be minimized. Therefore, effective treatment for DR can be administered only in the first stages of the disease. In this paper we have proposed a method for automatic detection of DR using Extreme Learning Machine (ELM).

Autotmatic detection of DR using extreme learning machine: The proposed system has three main stages viz, preprocessing, feature extraction and classification of retinal images with grading. Figure 3 shows the block diagram of proposed work. The preprocessing step reduces any imperfections and generates images more suitable for extracting the features. We have considered the features like the area of blood vessels, exudates, microaneurysms and statistical texture properties like mean, standard deviation and third momentum. The goal of feature extraction is to find a subset of informative variables from very high dimensional image for simplifying classification problem. In the last step the extracted features are given as input to the classifier and the retinal images are classified based on their severity like No DR, Mild DR, Moderate DR and Severe DR.

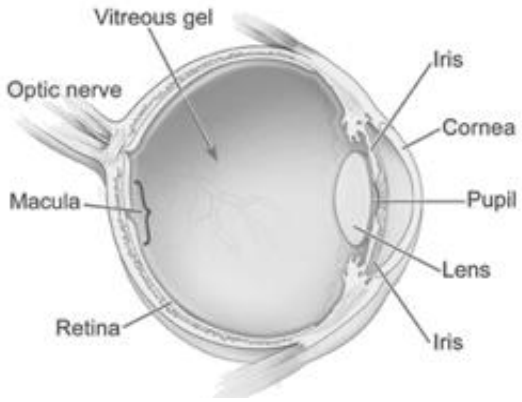


Fig. 1: Anatomy of human eye

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

Green channel extraction: In order to enhance the contrast of the retinal images, some information is commonly discarded before processing such as the red and blue components of the image. Consequently, only the green band is extensively used in the processing as it displays the best vessels/background contrast and the greatest contrast between the optic disc and the retinal tissue. In addition, the subsequent feature extraction process will be made simpler if a single channel image is used. The vessels are visible in the red channel but this channel usually contains too much noise or it is simply saturated, since most of the features emit a signal in the red channel (ElAbbadi and Saadi, 2013). Thus, the green pixel values are extracted from the input image and stored in the matrix form using Eq. 1:

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

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 Fig. 4a-e.

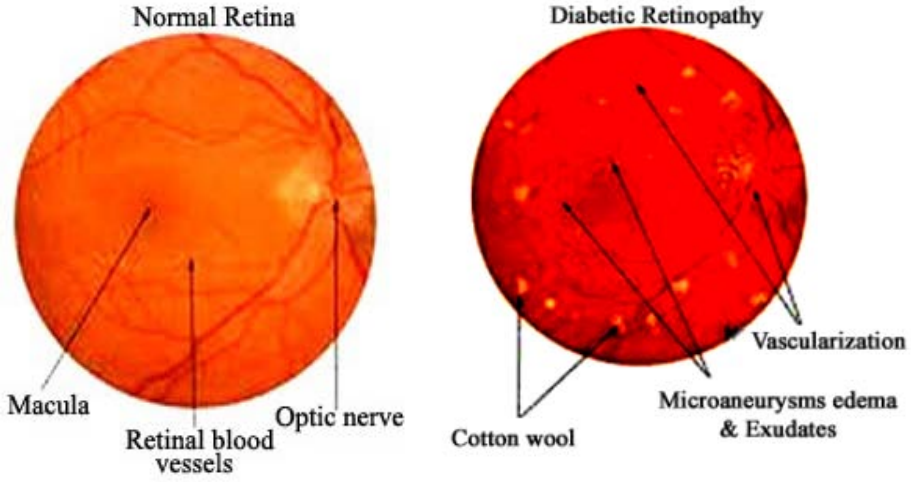


Fig. 2: Normal and diabetic retina

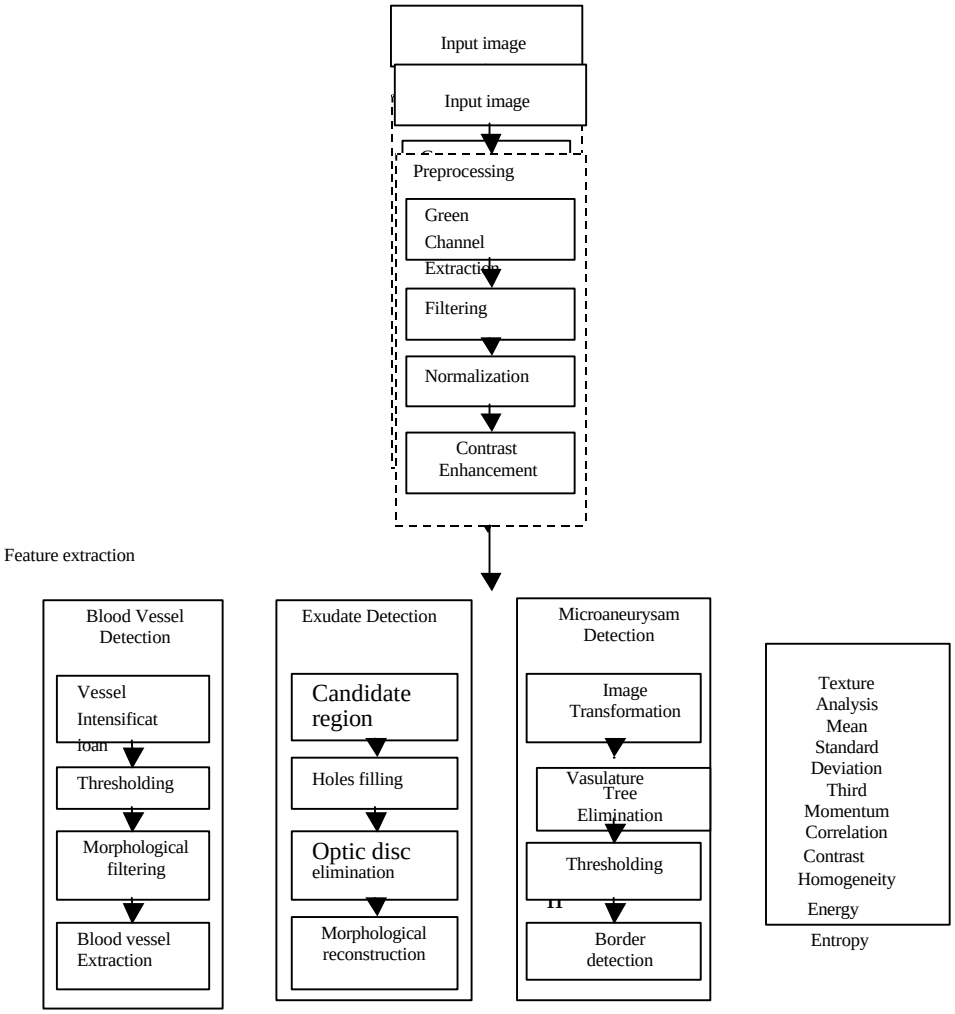


Fig. 3: Architectural flow of proposed work

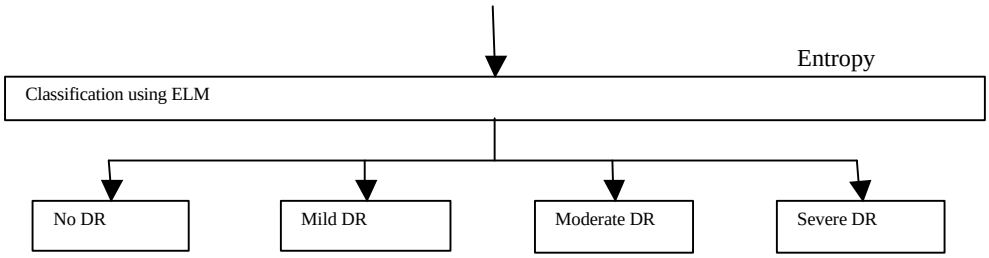


Fig. 3: Continue

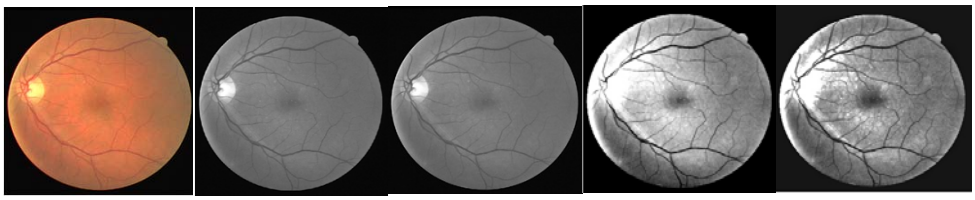


Fig. 4: Illustration of steps of preprocessing: a) Original image; b) Green channel extraction; c) Filtered image; d) Normalized image and e) Contrast enhancement

Filtering: Retinal images after acquisition are generally noisy, low contrast with non-uniform illumination and therefore it is necessary to deepen the contrast of these images to provide a better transform representation for subsequent image analysis step. Median filtering is a nonlinear method used to remove noise from image

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

where s,t represents the pixel value present in the moving window and represents the pixels present in the original image. In median filtering, the neighboring pixels are ranked according to brightness and the median value becomes the new value for the central pixel. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixel.

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. Unlike histogram equalization, contrast stretching is restricted to a linear mapping of input to output values. The result tends to avoid the artificial appearance of equalized images.

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

As a result, the contrast of the image was increased as shown in Fig. 5.

Contrast enhancement: To the resultant image, Contrast Limited Adaptive Histogram Equalization (CLAHE)

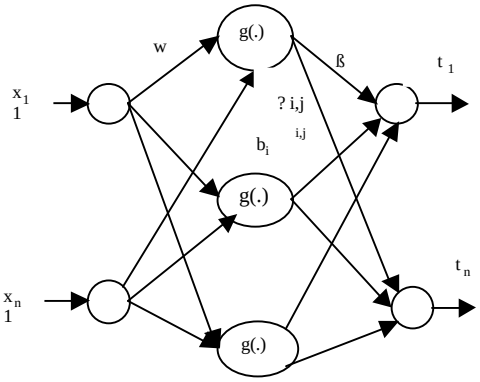


Fig. 5: The architecture design of ELM

(Hassan *et al*., 2012) is applied to enhance the contrast adaptively across the image by limiting the maximum slope in the transformation function. The CLAHE DR image is median filtered to smoothen the background inhomogenities that were resultant from the enhancement algorithm, to reduce impulse noise and the ability to preserve edge information of resultant image and its output is shown in Fig. 5.

Blood vessel detection: Features such as swelling leaking of fluid in blood vessels, and growth of abnormal new blood vessels have to be detected automatically for effective treatment of DR patient but it is a challenging task. The contrast of retinal image diminishes as distance of a pixel from the centre of the retinal image. Also the presence of noise, the variability of vessel width, and the presence of some pathological lesions makes the task more difficult. In this study, algorithms based on mathematical morphology are developed for retinal vessel segmentation. Figure 5 shows the result of extracting blood vessels.

Vessel intensification: In the proposed approach, first the vessels in the retinal image are strengthened using top-hat transform. The enhancement effect of a top-hat transformation is due to the estimation of local background by a morphology opening operation which is subtracted from the original image resulting in enhanced vessels (Zhang and Chutatape, 2005):

$$t_h(f) = (f \circ b) - f \quad (4)$$

Where:

$t_h(f)$ = The tophat transformation
$\circ$ = The opening operation
b = The structuring element
f = The filtered image

Thresholding and filtering: To remove the unnecessary details, thresholding (14) technique is applied that converts the image into binary image. Thresholding is used to extract an object from its background by assigning an intensity value T(threshold) for each pixel such that each pixel is either classified as an object point or a background point. Pixel based global thresholding was applied and it is defined as follows:

$$h(i,j) = \begin{cases} 0 \text{ if } v < T \\ 1 \text{ if } v \geq T \end{cases} \quad (5)$$

Where:

T = The threshold
v = The pixel value

Then, the smallest details are removed using morphological filters (ElAbbadi and Saadi, 2013).

Blood vessel extraction: Blood vessel recognition is determined by 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 (ELAbbadi and Saadi, 2013). Circularity of the shape of the region is defined by Eq. 6:

$$\text{Circularity} = (4 \times 3.14)\frac{\text{Area}}{(\text{Perimeter})^2} \quad (6)$$

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 are not considered as blood vessels and it is removed. The output of the image is shown in Fig. 6a-c.

Exudates detection: Exudates, the most commonly occurring lesions are associated with patches of

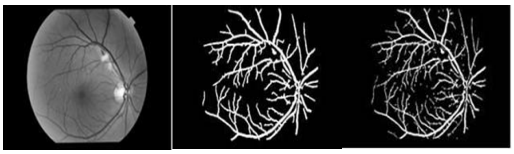


Fig. 6: Illustation of blood vessel detection: a) Green channel image; b) Morphological reconstruction and c) Blood vessel extraction

vascular damage with leakage. It can be identified as white or yellowish areas with varying sizes, shapes, and locations. They normally appear near the leaking capillaries within the retina. The main cause of exudates is proteins and lipids leaking from the blood into the retina via damaged blood vessels. Exudates are one of the lesions of diabetic retinopathy and they have similar contrast and colour with that of optic disc. Identification and removal of the optic disc helps in improving the classification of exudates regions i.e. the candidate regions.

Hole filling: All the pixels that are probable to be exudates pixels are considered as candidate region. To get the exudates as enclosed area, filling of the holes (Sopharak *et al*., 2010) is done by reconstructing the image from its borders to obtain the whole candidate regions rather than their borders. A hole may be defined as a background region surrounded by a connected border of foreground pixels. The flood filling operation changes the connected background pixels (0's) to foreground pixels (1's), stopping when it reaches object boundaries. The candidate region is dilated in order to ensure that there are background pixels next to exudates that are included in the candidate regions.

Optic disc elimination: The optic disk occupies maximum area in the image and hence it is eliminated by connected component analysis that is an image segmentation technique in which image pixels with same intensity are grouped into components based on pixel connectivity. Since the optic disk (Suero *et al*., 2013; Lu and Lim, 2011) occupies maximum area in the image, by using connected component properties the maximum area is eliminated. A region R (subset of S) is said to be connected under c (s) if for all s, there exists a sequence of M pixels, $s_1, \ldots, s_M$ such that:

$$s_1 \in c(s), s_2 \in c(s_1), \ldots, s_M \in c(s_M - 1), r \in c(s_M) \quad (7)$$

i.e., there is a connected path from s to r.

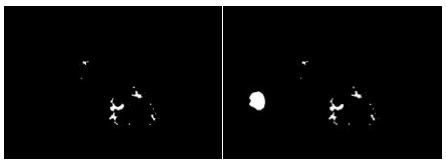


Fig. 7: Exudate detection: a) Presence of optic disk with exudates and b) Presence of exudates

Morphological reconstruction: Reconstruction by dilation reconstructs bright regions in grayscale images and reconstructs particles in binary images. Starting at the marker points, neighboring pixels are reconstructed by spreading the brightness value. Reconstruction by dilation starts with the maximal gray valued pixels of the marker and reconstructs the neighboring pixels ranging from 0 to the maximal valued pixel. Figure 7a is the mask image and 7b shows the optic disk eliminated image.

Microaneurysm detection: A Microaneurysm (MA) is a tiny aneurysm, or swelling, in the side of a blood vessel. In people with diabetes, microaneurysms are sometimes found in the retina of the eye. These miniature aneurysms can rupture and leak blood. Some research indicates that these microaneurysms can predict the progress of diabetic retinopathy, a condition in which blood vessels of the retina are damaged by diabetes, which can lead to blindness. Microaneurysms whose size ranges from 25-100 μ are dark reddish in colour and occur in the macula can lead to significant visual impairment and they are in the low intensity regions. Hence detection is complicated by their small sizes, the presence of retinal vessels, and their similarity to another type of retinal abnormality haemorrhages.

Image transformation: A pre-processed retinal image is used as preliminary image for MA detection. The extended-minima transform is the regional minima of h-minima transform. It is applied to the image. This transformation is a thresholding technique that brings most of the valleys to zero. The h-minima transform suppresses all the minima in the intensity image whose depth is less than or equal to a predefined threshold. The output image is binary images with the white pixels represent the regional minima in the original image. Regional minima are connected pixels with the same intensity value, whose external boundary pixels all have a higher value. The output is a binary image. The extended minima transform on the image with threshold value is given by Eq. 8:

$$f_{out} = exmin\left(f_{img}, \alpha_2\right) \quad (8)$$

where the selection of threshold is most important. Where the higher value of will decrease the number of regions and a lower value of will increase the number of regions.

Vasculature tree elimination: Top hat transformation enables us to extract small or thin, bright or dark objects from a varying background. It is a composite operation that extracts small elements and details from given images Huang *et al*. (2012). It is the difference between an input image and its opening and is used for extracting small or narrow, bright or dark features in an image. It is useful when variations in the background mean cannot be achieved by a simple threshold. The top-hat transformation of a gray-scale image f is defined as f minus its opening:

$$T_{hat}(f) = f - (f \circ b) \quad (9)$$

Thresholding: For highlighting and removing noise, the Morphological open function is carried out by using median filter and Otsu's thresholding algorithm. Otsu's thresholding method is one of the many binarization algorithms which assume that the image contains two classes of pixels, i.e. the pixels that either falls in foregroun or background following bi-modal distribution of gray-level values. Otsu's method selects the threshold by minimizing the within-class variance of the two groups of pixels separated by the thresholding operator. The following equations describe the Otsu's algorithm: The weighted within class variance is calculated using Eq. 10:

$$\sigma^2_{between}(T) = W_B(T)W_o(T)\left[\mu_B(T) - \mu_o(T)\right]^2 \quad (10)$$

Where:

B = The background of the image
o = The object of the image
T = The threshold value
W = The weight
μ = The combined mean

Here, the class probabilities are estimated using Eq. 11 and 12 and the class mean are calculated using Eq. 13 and 14:

$$W_B(T) = \sum_{i=0}^{T-1} p(i) \quad (11)$$

$$W_o(T) = \sum_{i=T}^{L-1} p(i) \quad (12)$$

$$\mu_B = \sum_{i=0}^{T-1} \frac{ip(i)}{p(i)} \quad (13)$$

$$\mu o = \sum_{i=T}^{L-1} \frac{ip(i)}{p(i)} \quad (14)$$

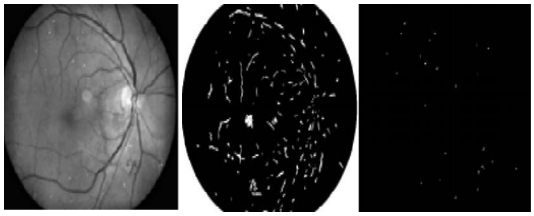


Fig. 8: MA detection: a) Green component image; b) After extended minima transform and c) Microaneuruysm

Border detection: To detect Microaneurysm boundaries objects with size smaller or equal to 10 pixels are considered because the MA diameter is <125μm. The size of MA usually ranges from 12-100 μm; those greater than 30 μm is visible ophthalmoscopically. They are not to be >125 μm. Hence to detect Microaneurysm boundaries objects with size smaller or equal to 10 pixels are considered because the MA diameter is <125 μm. Figure 7a-c shows the microaneurysms detected from the green component image.

Texture analysis: Texture of an image helps to segment images into regions of interest and to classify those regions. In some images, it can define characteristic of regions and critical in obtaining a correct analysis (Yilmaz and Tekin, 2013). It gives information about the arrangement of surface pixels and their relationship with the surrounding pixels. The main types of texture analysis are structural, statistical and spectral. The texture features (Huang *et al*., 2012) considered for this work are mean, standard deviation and third momentum.

Mean is the measure of average intensity; standard deviation represents the average contrast while third momentum gives the measure of skewness of a histogram. Entropy is a feature which measures the randomness of grey-level distribution. 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 neighbour over the whole image. Homogeneity reflects the uniformity of several pixels in an image and expresses how similar all of them are. In correlation, the value of an output pixel is also computed as a weighted sum of neighbouring pixels. The correlation operation therefore returns a measure of how correlated a pixel is to its neighbour over the whole image and they are defined as follows:

$$\text{Mean } (\mu) = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} iP_{i,j} \tag{15}$$

$$\text{Standard deviation } \sigma = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{i,j}(1-\mu)^2} \tag{16}$$

$$\text{Third momentum } m_g = \sum_{i=0}^{N-1}(zi-m)^3 p(z) \tag{17}$$

$$\text{Entropy} = -\sum_i\sum_j P[i,j]\log P[i,j] \tag{18}$$

$$\text{Energy} = \sum_i\sum_j P^2[i,j] \tag{19}$$

$$\text{Contrast} = \sum_i\sum_j P(i-j)^2 P[i,j] \tag{20}$$

$$\text{Homogeneity} = \sum_i\sum_j \frac{P[i,j]}{1+|i-j|} \tag{21}$$

$$\text{Correlation} = \sum_{i,j}\frac{\left[(i-\mu i)\times(j-\mu j)\times p(i,j)\right]}{\left[\sigma_i\times\sigma_j\right]} \tag{22}$$

Where:

$P_{i,j}$ = Represents the pixel value at location I

N = Denotes the number of gray levels, epresents the corresponding histogram for I = 0,1,2,…,N-1, Z represents random variable denoting a gray level

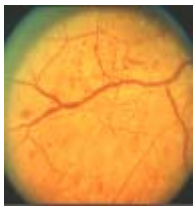
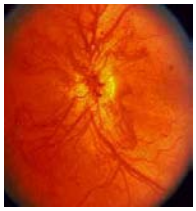
m_g = Deneotes the integer power exponent that defines the moment order

Severity detection: After the detection of area of blood vessels, microaneurysms and exudates, the retinal images were classified based on their severity using the count of detected blood vessel, microaneurysms, exudates and other texture features. Those detected features were used as the input parameters to single layer feed forward neural network for classification into different retinopathy stages. The activation function like sine, gaussian, sigmoidal etc., can be chosen for hidden neuron layer and linear activation functions for the output neurons. The size, count and distribution of microaneurysms, exudates and hemorrhages are used to predict the severity of DR (Table 1).

Extreme learning machine: The Extreme Learning Machine (ELM), a single hidden layer neural network is an extremely fast learning algorithm with good generalization performance. In comparison to the backpropagation learning algorithm which requires the setting of several user-defined parameters and may produce local minima, the ELM requires setting of one parameter, and produces a unique solution for a set of randomly assigned weights. ELM is a simple tuning-free three-step algorithm used for classification and regression.

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 figures given in Table 1.

Table :1 Shows the standard followed for the assignment of severity levels of DR

Features	No DR	Mild DR	Moderate DR	Severe DR
Microaneurysms	No MA	1<MA≤5	≤5 MA≤10	≥15
Hemorrhages	0 H	0H	0<H≤ 5	H>15
Exudates	0E	All small size≤5	3≤E<5	E≥5
Sample image				

shown in the Fig. 4, 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 (Gu *et al*., 2009) are assigned randomly. 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 where, is called the hidden layer output matrix of the neural network, 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 the activation function g(x) and the number of hidden nodes:

- Assign randomly input weight and bias for and define hidden layer node number
- Calculate the hidden layer output matrix H
- Calculate the output weight $\hat{a}$:

Classification using ELM: For our proposed method we have given nine parameters namely, area of blood vessels, exudates, microaneurysms and the texture features n as input to the ELM classifier. The input parameters were used for classification of the retinal image based on its severity. In this algorithm activation function of hidden neurons were chosen as sigmoidal activation function. Training areas must be selected for each of its classes. ELM based classifier performs training and testing faster than convention neural network based classifier. It is a Multi-class classification where number of output neurons will be automatically set equal to number of classes. The output consists of four different classes showing the retinal images which have no DR, mild DR, moderate DR and severe DR.

METERIALS AND METHODS

Implementation of ELM for DR Analysis: 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 [10] 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 consists of 89 images of which 84 contain at least mild non-proliferative signs of the diabetic retinopathy and 5 are considered as normal which do not contain any signs of the diabetic retinopathy 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 severity using the value of the extracted features.

Results of preprocessing: This study shows the output of the steps discussed in study as. The green channel of the image is extracted and the noises are eliminated using median filtering. Followed by filtering, normalization was carried out to make full use of possible intensity values. In order to further enhance the image CLAHE was carried out and the results of these steps are shown below in Fig. 9.

Results of feature extraction: As seen earlier the features considered for our proposed method is the area of blood vessels, exudates and microaneurysms and texture features. The total number of white pixels present in the image after extracting blood vessels, exudates and microaneurysms gives the area. The figure shows the result of blood, exudates and microaneurysms detection.

Table 2: Set of Features used for grading severity of DR classification

Feature	Description
Area of blood vessels, Exudates, microaneurysms	Their count helps in analysis of retinal image
Mean	Measure of average intensity
Standard deviation	Finds the average contrast
Third momentum	Skewness of a histogram
Energy	Mean squared value of the image
Contrast	Intensity contrast between a pixel and its neighbour over the whole image.
Homogeneity	Gives the uniformity of several pixels in an image
Entropy distribution	Measures the randomness of grey-level
Correlation	Weighted sum of neighbouring pixels

Table 2 shows the features considered for the analysis of retinal image.

RESULTS AND DISSCUSION

Table 3 shows the classification accuracy obtained by different classifiers using different set of features. When few combinations of features were considered the classification accuracy is not high. The classification accuracy was high when we consider all the extracted features when using the classifiers like BPNN, SVM and ELM.

Training and 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. 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 4 shows the comparison of training time and testing time taken for classification. The ELM classifier has taken few seconds for training the data when compared with other classifiers (Table 5).

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 (Table 6):

$$\text{Misclassification rate}=\frac{\text{Number of wrongly classified images}}{\text{Totalnumber of images}}\times 100 \quad (23)$$

The misclassification rate for BPNN, SVM and ELM is 0.28, 0.13 and 0.01, respectively. The following Fig. 9 shows an accuracy of 96% is achieved when the number of hidden neurons is 80.

Table 3: Classification results for different combinations of features

	Classification accuracy (%) using		
Features	BPNN	SVM	ELM
BV+MA	69.8	72.33	74.3
BV+Exudates	70.12	70.17	72.6
Exudates+MA	65.4	68.6	71.2
BV+MA	74.4	76.6	78.9
Texture Features(TF)	73.2	75.43	75.5
TF+BV	72.5	75.82	76.4
TF+Exudates	66.5	69.74	69.85
TF+MA	73.6	75.53	77.64
TF+BV+Exudates	68.9	71.37	73
TF+Exudates+MA	79.4	83.14	88.4
TF+BV+MA	80.2	83.9	85.6
All features	81.2	90.6	96.2

Performance validation: In this study, 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 and classification accuracy. The metrics used for analyzing the performance are discussed below.

Sensitivity and specificity: Sensitivity means the percentage of abnormal funduses classified as abnormal by the procedure while specificity gives the percentage of normal funduses 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:

$$\text{Sensitivity} = \text{TP/TP+FN} \quad (24)$$

$$\text{Specificity} = \text{TN/TN+FP} \quad (25)$$

$$\text{Accuracy} = (\text{TP+TN})/(\text{TP+TN+FP+FN}) \quad (26)$$

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 also classified as abnormal by the algorithm. Similarly, a true negative refers to negative pixels correctly labeled as negative. A false positive means that the fundus is actually normal, but the procedure classified it as abnormal whereas false negative indicates the procedure which classified the screened fundus as normal but it is really abnormal (Table 7).

Where Se is the specificity, Sp is the specificity Ppv is the Positive predictive value, Npv is the negative predictive Value and Acc denotes accuracy. Ppv and Npv is defined by the following equation.

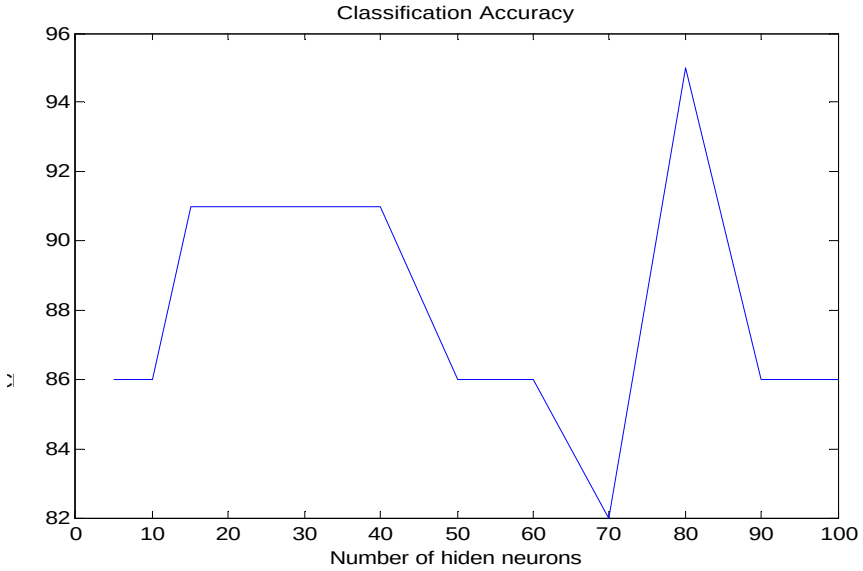


Fig. 9: Hidden neurons vs. classification accuracy

Table 4: Comparison of training and testing time for DIARETDB1 database

Classifiers	No training images	No testing images	# correctly classified images	correctly classified images(%)
Back propagation neural network	20	20	16	80
Support vector machine	20	20	17	85
Extreme learning machine	20	20	19	95

Table 5: Comparison of training and testing time for DRIVE Database

Classifiers	No training images	No testing images	No 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

Table 6: Classification accuracy

	Neural networks		SVM		ELM	
Parameters	Drive	DiaretDB1	Drive	DiaretDB1	Drive	DiaretDB1
Training time (sec)	9.74	9.7969	0.163	0.1563	0.301	0.313
Testing time(sec)	0.092	0.0938	0.0431	0.0469	0.0627	0.0625

Table 7: Performance Results on sample images in DRIVE and DIARETDB1 Database images

Image	Se	Sp	Ppv	Npv	Acc
0.001	0.9152	0.9671	0.8234	0.9876	0.9761
0.002	0.9455	0.9453	0.8257	0.9377	0.9751
0.003	0.8576	0.9532	0.8239	0.9701	0.9635
0.004	0.89245	0.9855	0.8369	0.9351	0.9761
0.005	0.9331	0.9832	0.8249	0.9538	0.9589
0.006	0.9432	0.9626	0.8337	0.9652	0.9632
0.007	0.9139	0.9574	0.8437	0.9541	0.9761
0.008	0.8932	0.9692	0.8569	0.9498	0.9686
0.009	0.9532	0.9856	0.8471	0.9659	0.9652
0.010	0.9239	0.9517	0.8381	0.9589	0.9765

Table 8: Comparison of sensitivity and specificity

Source	Sensitivity (%)	Specificity (%)	Accuracy (%)
Walter *et al.* (2006)	81.6	99.9	99.9
Sopharak *et al.* (2008)	70.6	98.0	94.5
Shadgar	94.9	93.8	95.3
Atul Kumar	97.1	98.3	99.1
Osareh *et al.* (2010)	93.4	82.7	90.1
Proposed method	96	95	95

$$Ppv = \frac{T_P}{(T_P + F_P)} \quad (27)$$

$$N_{pv} = \frac{T_N}{(T_N + F_N)} \quad (28)$$

Performance comparison: Table 8 compares our approach in terms of sensitivity and specificity values obtained using different methods and our proposed method has 96 and 95% 0f sensitivity and specificity, respectively.

CONCLUSION

Detection of diabetic retinopathy at early stage can reduce the development of diseases significantly. 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 preprocessing the concept of

morphological image processing was applied to the enhanced image for feature extraction. We have calculated the area of blood vessels, microaneursyms and exudates. Along with those values, the texture features were identified and used for retinopathy detection. These features were fed as input to the ELM classifier for classifying the severity of diabetic affected 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 96%. As future work, optimal feature selection along with the advanced classification techniques can be used for producing reduced complexity.

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