Longitudinal time-series of color retinal Fundus Image for Diabetic Retinopathy

C.Jayakumari
SSN College of Engineering, Chennai

R.Maruthi
SSN College of Engineering, Chennai

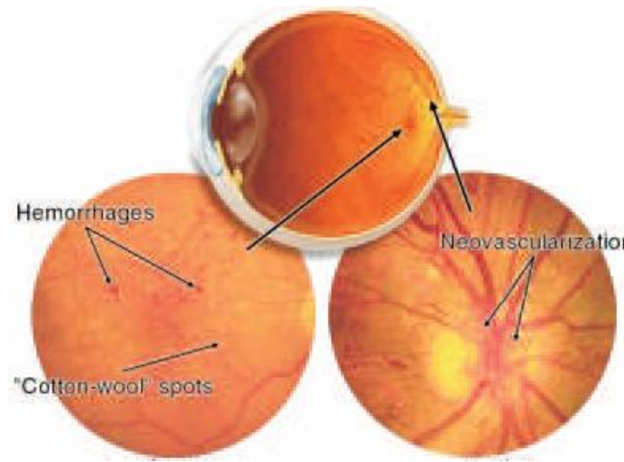
ABSTRACT
Diabetic retinopathy is a severe and widespread eye disease that affects many diabetic patients and it remains one of the leading causes of blindness Usually diabetic retinopathy is asymptomatic in the premature phase and intensifies as it grows. Hence, routine screening is essential to reduce the further complication to a significant level. In this paper, a state-of-art image processing techniques to automatically detect the occurrence of hard exudates in the fundus images are discussed. After the adaptive contrast enhancement as preprocessing stage, fuzzy C-means algorithm has been applied to extort the same. The standard deviation, intensity, edge strength and compactness of the extracted features of the fundus images have been fed as an inputs into a recurrent Echo state neural network to classify the extracted features as true candidate or not. A total of 50 images have been used to find the exudates and out of which 35 images consisting of both normal and abnormal are utilized to train the neural network and obtain 93% sensitivity and 100 % specificity.

General Terms
Pattern Recognition, Image Processing, Neural network.

Keywords
Diabetic Retinopathy, Hard exudates, Fuzzy C-Means, ESNN

1. INTRODUCTION
The World Health Organization (WHO) approximates that 135 million people have diabetes mellitus worldwide and that the number of people with diabetes will intensify to 300 million by the year 2025 [1]. Patients with diabetes are prone to develop many eye related problems and the diseases that affect on the retina are the main threat to vision. There are no symptoms at the initial stages. Periodic eye examination is the only way to detect early disease and prevent further deterioration of vision. Complication of diabetes, causing abnormalities in the retina can worsen the disease drastically and it can even cause blindness [2]. So there is a significant need to develop an inexpensive, sophisticated screening program for the Diabetic Retinopathy to reduce the economic and social consequences of vision loss.

Ophthalmologists make use of the fundus images to study the eye diseases like diabetic retinopathy. These images provide information on pathological changes caused by the eye diseases, which are an early symptom of certain systemic diseases, such as diabetes and hypertension [3]. Figure 1 (a) shows a typical retinal image labeled with various feature components of Diabetic Retinopathy and Figure 1 (b) a normal retinal image.



Background Diabetic Retinopathy

Proliferative Diabetic Retinopathy

Figure-1 (a)Diabetic Retinopathy features

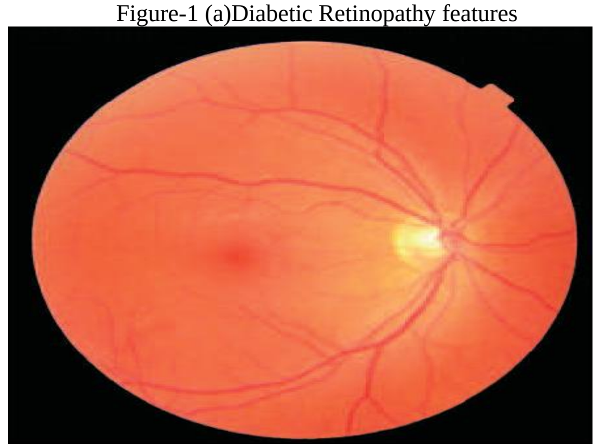


Figure 1 (b) Normal Image

Microaneurysms are tiny swelling in the wall of a blood vessel. It becomes visible in the retinal capillaries as a small, round, red spot. It is generally found in diabetic retinopathy, retinal vein occlusion or absolute glaucoma. This may also lead to big blood clots called hemorrhages. Hard exudates are yellow lipid deposits, which show as bright yellow lesions. The bright circular region from where the blood vessels emanate is called the optic disk. The fovea defines the center of the retina, and is the region of highest visual acuity. The spatial distribution of exudates and micro aneurysms and hemorrhages, particularly in relation to the fovea can be exploited to conclude the severity of diabetic retinopathy.

Several researchers have been explored in this area using various algorithms. Jagadish Nayak et.al. employed image preprocessing, morphological processing techniques and texture analysis methods on the fundus images to detect the features such as the area of hard exudates and the area of blood vessels[11]. Garcia.M et.al. extracted a set of features from image regions and selected subset which best discriminates between hard exudates and the retinal background. The selected features were then used as an input to a multi layer perceptron classifier to obtain a final segmentation of hard exudates in the image[12]. J.Anitha et.al has used texture-based feature extraction and the application of Kohonen neural networks for pathology identification using 420 abnormal retinal images and achieved an average sensitivity and the specificity values of 96% and 98% [10]. Akara sopharak et. Al. has explored on the morphological extraction of hard exudates[13]. .Sinthanayothin et.al. reported the result of an automated detection of diabetic retinopathy on digital fundus image by recursive region growing segmentation algorithm [14]

The automated diabetic retinopathy diagnosis system has been developed using color retinal images obtained from Swamy Eye Clinic in Chennai, Tamil Nadu, and India.

This paper elucidates an algorithm that facilitate reliable, and fully automated detection of hard exudates of color retinal fundus images exhibiting diabetic retinopathy.

The sequence of steps necessary for the segmentation and classification of hard exudates by implementing preprocessing using Adaptive histogram Equalization (CLAHE), segment the image using Contextual clustering algorithm and ESNN has been utilized to classify the features and it is demonstrated in figure 2.

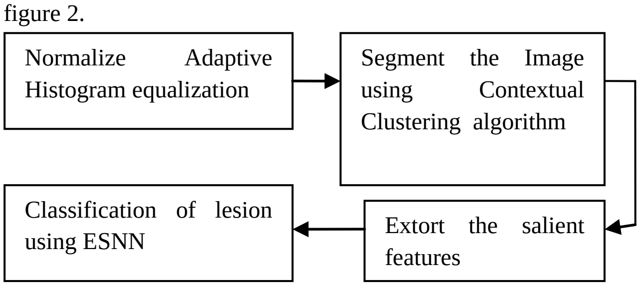


Figure 2 Block diagram of hard exudates Detection

2. PREPROCESSING

The acquired color retinal images are normally of different qualities and need illumination equalization to augment the image quality. The idea of preprocessing is to get rid of the noise and undesired regions from the retinal image. This is essential for the reliable mining of features and abnormalities as feature extraction and abnormality detection algorithms, otherwise the system produce poor results in the presence of noisy background.

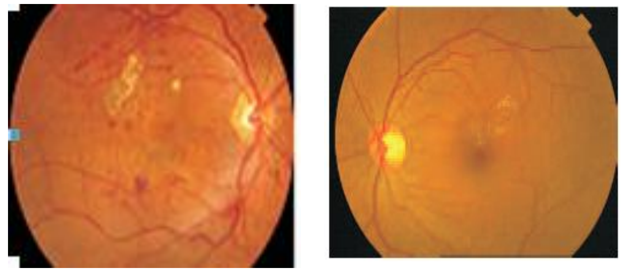


Figure-3 (a)original image-1 (b) Original image-2

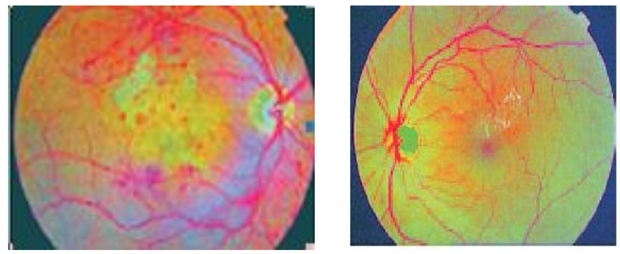


Figure-4 (a)Preprocessed image-1 (b) preprocessed image-2

Firstly, original image's Red, Green and Blue (RGB) space was transformed to Hue, Saturation and Intensity (HSI) space. A median filtering operation was then applied on this I band to reduce noise before a Contrast-Limited Adaptive Histogram Equalization (CLAHE) [4] was applied for contrast enhancement. Then contrast-limited adaptive histogram equalization (CLAHE) is used to enhance contrast of small regions in an image. CLAHE operates on small regions in an image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram of the specified 'Distribution' parameter. The neighboring tiles are then combined by means of bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image. The output of the preprocessing along with normal images are depicted in the figure-3(a) , (b) and figure 4(a), (b)..

3. FUZZY C-MEANS CLUSTERING

The color retinal images were segmented using Fuzzy C-Means (FCM) clustering and the segmented regions were classified using Echo State Neural Network [ESNN]. FCM clustering is an overlapping clustering algorithm; each point may belong to two or more clusters with different degrees of membership. In this case, data will be associated to an appropriate membership value. It is based on minimization of the following objective function [5]

$$J = \sum_{I=1}^{N} \sum_{J=1}^{C} u_{ij}^{2} \, \| X_i - C_i \|^{2} \quad (1)$$

where N is number of features and C is number of clusters, *uij* is the degree of membership of *xi* in the cluster *j*, *xi* is the *i*th of d-dimensional measured data, *cj* is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership *uij* and the cluster centers *cj* by the following equations respectively.

$$u_{ij} = 1 / \sum_{1}^{C} [\|x_i - c_i\| / \| x_i - c_k \|]^2 \quad (2)$$

$$C_i = \frac{\sum_{I=1}^{N} u_{ij}^{2} x_i}{\sum_{I=1}^{N} u_{ij}^{2}} \quad (3)$$

The result from FCM clustering is shown Figure 5 & 6.

4. POST PROCESSING

The result obtained from the above algorithm contains some misclassified pixels which appeared as undesirable noise in the classified image, therefore, post-processing is mandatory to attain a perfect segmented image lesions. In order to extract the features segmented regions are labeled using bwlabel function using Matlab then the features of the corresponding regions like standard deviation, intensity, edge strength and compactness [6] are estimated using the region props function and classified using a Echo State Neural Network .

Figure5 a) Image- Hard Exudates (b) Segmented Image

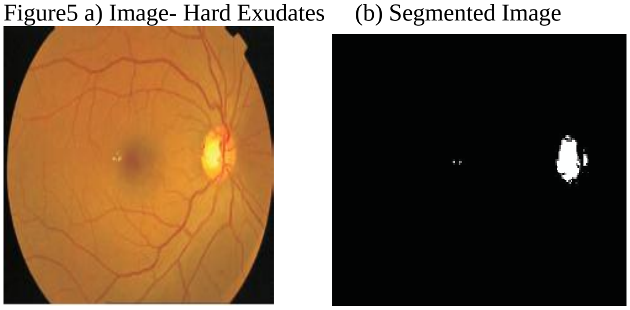


Figure 6 a) Image- Hard Exudates (b) Segmented Image

4.1 Echo State Neural Network

Echo State Neural Network (ESNN) [7] possesses a highly interconnected and recurrent topology of nonlinear PEs that constitutes a "reservoir of rich dynamics" and contains information about the history of input and output patterns. The topology of the network is shown in Figure. 5. The outputs of internal PEs (echo states) are fed to a memory less but adaptive readout network (generally linear) that fabricates the network output. The exciting property of ESNN is that only the memory less readout is trained, whereas the recurrent topology has fixed connection weights. This decreases the complexity of RNN training to simple linear regression while preserving a recurrent topology, but obviously places important constraints in the overall architecture that have not yet been fully studied. The ESNN topology specified in this work is {2 x no. of reservoirs x 1 }, where two nodes are in the input layer, one in the output layer and any number of reservoirs in the hidden layer. The connections between input-hidden layers, hidden-output layer are initialized with random numbers.

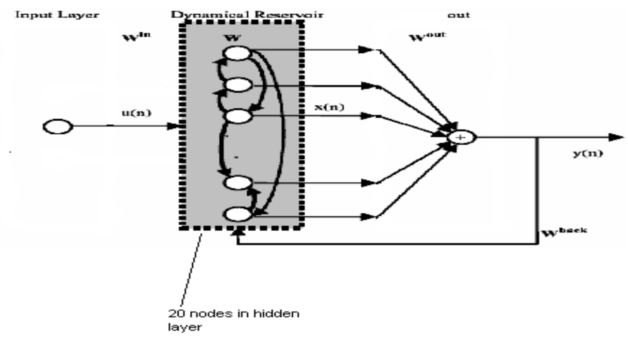


Figure 7 Architecture of Echo State Neural Network

The training of the ESNN is done with choosing initial random weights in a range of 0.25 to 0.55. The random weights are chosen within a small range for easier quicker settlement of final weights and also to prevent the network from further oscillation.

4.2 Determining the reservoir weight Matrix

1. Generate a sparse random matrix.
2. Scale the matrix by its highest eigen value
3. Multiply the matrix by α, known as the spectral radius, [∞ € 0,1]

$$W = \frac{\alpha * W_0}{| \lambda_{\max} |} \quad (4)$$

ESNN is composed of two parts, a fixed weight (k W k < 1) recurrent network and a linear readout. The value of the input unit at time n is

$U(n)=[u1(n), u2(n)\ldots..uM(n)]^T$. (5)

The internal units are

$x(n)=[x1(n), x2(n)\ldots..xN(n)]^T$ (6)

and Output units are

$y(n)=[y1(n), y2(n)\ldots..yL(n)]^T$ (7)

5. EXPERIMENTAL RESULTS

Once the retinal images are segmented, each image is characterized by its corresponding segmented region. It is necessary to discriminate the extracted region as exudates or nonexudates. This is accomplished by extracting a set of features for each region and then the regions are classified based on the generated feature vectors. The selected sets of features are standard deviation of the intensity, mean, intensity, size, edge strength and compactness [7].

Each image was classified as normal or abnormal according to the presence or absence of exudates. A patient was classified as abnormal if the presence of exudates is found else it is classified as normal. 70% of the images are used to train the neural network and the remaining images are used to evaluate the performance of the system. The results are shown through an ROC curve by taking the true-positive, true-negative, false-positive false-negative and by calculating the sensitivity and specificity [9].

The various results obtained by using CC and ESNN for hard exudates are described here. The performance of the result is exhibited through ROC curve and it is depicted in the following figure. Figure 8 & 9 shows the exudates superimposed on the original image and figure 10 shows the ROC curve. The images used in this work were obtained from a popular eye clinic in Chennai, India. The proposed algorithm has yielded a reasonable results and sample output is shown in figure 6.

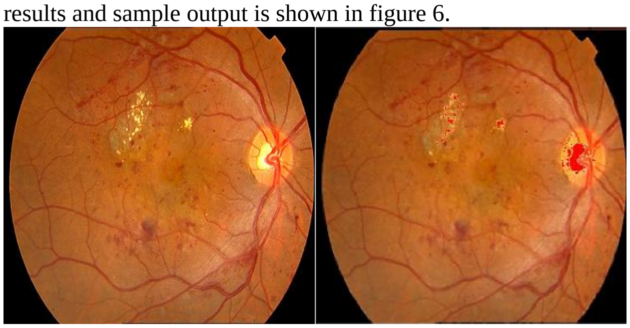


Figure 8 (a) Exudates (b) imposed on the original image

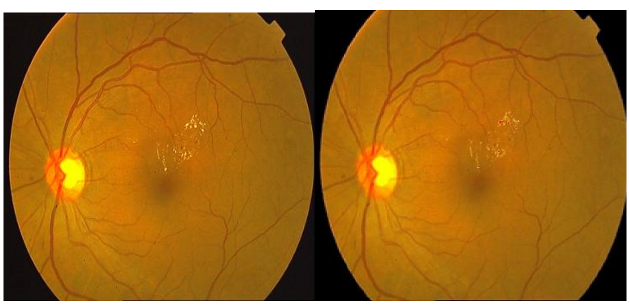


Figure 9 (a) Exudates (b) imposed on the original image

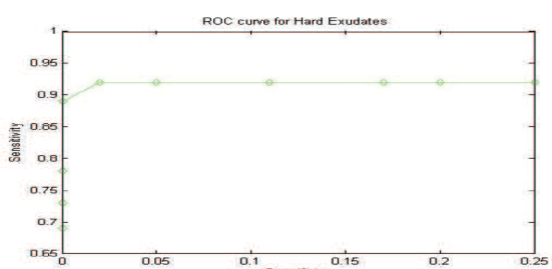


Figure 10 ROC curve for hard exudates segmentation

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