

NEW AUTOMATED SYSTEM FOR SEVERITY JUDGMENT OF EARLY STAGE DIABETIC RETINOPATHY

Amritansh Saxena¹ | Gunjan Pahuja²

¹(M.Tech. Student, JSSATEN, Dr. A.P.J. Abdul Kalam Technical University, Lucknow, amssaxena@gmail.com)

²(Asth. Professor, JSSATEN, Dr. A.P.J. Abdul Kalam Technical University)

Abstract— There is an aggregating interest in development of the automatic medical diagnosis systems because of the advancement in the computer technology. The knowledge regarding health and disease is required at higher rate for the accurate medical diagnosis. The Diabetic Retinopathy is one of the most common problems that may lead to blindness and it can be prevented or cured if detected at the earlier stage. The presence of Diabetic Retinopathy can be detected by its different signs; the most distinctive is the presence of cotton wool and exudates which are bright lesions. It is necessary to localize the presence of optic disk and the structure of blood vessels. They play a very important role in the accurate detection and classification of cotton wools and exudates. This Research Work proposes a computer aided system which can be used for detection of exudates. The Research Work presents various algorithms for fundus retinal images preprocessing, blood vessel detection, optic disk localization, lesion detection, Detection of presence of diabetic retinopathy with the help of neural network. The developed method is tested on publically available STARE database and the performance metrics is calculated.

Keywords— Diabetic Retinopathy; Foveal avascular zone; Medical image analysis; Retinal fundus images; Panretinal Photocoagulation; Microaneurysms.

1. INTRODUCTION

Diabetic retinopathy is a Human Eye intimidating complication due to diabetes mellitus that affects the retina. Diabetic retinopathy severity can be viewed into five levels, namely NO Diabetic retinopathy, soft non-proliferative diabetic retinopathy, moderate NPDR, relentless NPDR and proliferative diabetic retinopathy.

Medical images analysis is a multidisciplinary study area, which covers image processing, machine learning pattern recognition and computer visualization. Retinal images are usually interpreted visually by the ophthalmologists in order to diagnose Diabetic Retinopathy. The system that can be used to analyze Retinal image can be evolved to assist ophthalmologists to make the diagnosis more efficiently. Diabetic retinopathy is the most common eye complication in diabetes.

The blood vessels in a human are very tiny in size and hence more prone. The deterioration of blood vessels starts occurring when the blood sugar levels are increased beyond the normal levels for a long-drawn-out time. This pathologically referred to as Diabetic retinopathy. In Diabetic retinopathy, the normal vision of a human is mired and as time passes by, the vision tends to become diminished fully means blindness occurred. Exudates, micro aneurysms and abnormalities in blood vessels are some features extracted to classify Diabetic retinopathy. Microaneurysms are small areas of balloon like swelling in the retinas tiny blood vessels. Diabetic retinopathy can also be detected from deviation in the structure or superfluous growth of blood vessels. Premature detection of these features helps the ophthalmologist to perceive the Diabetic retinopathy and also help in

preventing loss of sight. Revealing of these features is done from fundus images. The fundus images are taken from a special type of camera called fundus cameras. This detection helps the practitioner to decide on the severity of the Diabetic retinopathy and advise the required treatment to the patients. This paper gives insights in reviewing of some of the preprocessing techniques discussed in the literature. Also discussed various methods for detection and extraction of blood vessels, exudates and Microaneurysms are at last concluding paper with Automated Severity detection system for Diabetic retinopathy.

2. LITERATURE REVIEW

AlirezaOsareheta[2] suggested a common mode for the programmed detection of exudates which is created on the computational Intelligence method. The colored fundus retinal images were segmented by means of the fuzzy c-means clustering over the image .Feature vectors were mined from the image and classified by applying the multilayer neural network classifier.

Ege et al[4] the existence of noise in the image is removed by using median filtering, segment the bright lesions and the dark lesions by applying thresholding technique, accomplishes the region growing, and then recognizing the exudate sections with Bayesian.

AkaraSoparak[3] reported the result of an “automated detection of exudates” by using the low contrast digital images of the retinopathy patients with “the non-dilated” pupils by “Fuzzy C-Means clustering”. Four features were mined like intensity, hue, standard deviation on intensity image and a number of edge pixels and used on the input to “coarse segmentation using FCM clustering method.”

Gagnon et al [5] have presented an overview on the generic procedure in color retinal images for the detection of all important anatomical structures: the macula, the optic disk and the retinal work. "Test results show robustness against visual quality of the images and independently on the fact that the acquisition is macula or optic disk centered. A Success rate of 100% is reached for optic disk detection and 95% for macula detection." [5]

Niemeijeret al[8] In the color retinal images the bright lesion like exudates, cotton wool spots and drusen were distinguished. Initially the pixels were classified, subsequent in probability map that comprised the probability of each pixel to be portion of a bright lesion.

Osareh"etal[9] They report the development of a technique to quantitatively identify these arbitrary yellow patches in color retinal images automatically. After a color standardization and contrast improvement pre-processing step, the color retinal image is segmented using Fuzzy C-means clustering. Then categorize the segmented sections into two separate classes, exudates and non-exudates, relating the performance of various classifiers. They also trace the optic disk both to eliminate it as a candidate region and to magnitude its boundaries accurately since it is a significant landmark feature for ophthalmologists. Three different approaches are reported for optic disk localization based on template matching, least squares arc estimation. The classification could accomplish an overall diagnostic accuracy of 90.1% for identification of the exudate pathologies and 90.7% for optic disk localization."

T.Walteretal[12]"exudates were recognized from the green channel of the retinal images rendering to their gray level variation. Mathematical morphological techniques are used to determine the exudates curves. However the author overlooked particular types of errors on the boundary of the segmented exudates in their stated performances and did not distinguish exudates from cotton wool spots."

Abdel-Ghafar[1] this training groups out the developed methods of separating normal images from the abnormal images (cases of glaucoma or diabetic retinopathy). These could be used in a screening clinic to identify at risk patients. many image enhancement methods using estimated non-uniform background intensity of fundus image by applying median filtering to the green channel of the fundus image. Shade correction was generated by subtracting the result from the original green channel. "Fleming et al" had similar approach for Microaneurysms, but the green channel of the original fundus image was divided with the background intensity image. In addition, the shade corrected image was normalized for global image contrast by dividing with its standard deviation. Multiple local contrast enhancement methods were tested to improve detection accuracy. In hemorrhage detection, use of histogram specification applied to each individual RGB color component to normalize the colors between different fundus images. use of local contrast enhancement to equalize the intensity variation in fundus images. The fundus images were transformed from RGB color model to IHS color model and the local contrast enhancement was applied to the intensity component of the image.

Detection and classification methods: extracted the candidate finding areas by assigning posterior probability of being red finding for every pixel using Gaussian filter and

its derivates as features for k-nearest neighbor clustering. Shape and intensity properties of the candidate areas were used for more accurate abnormal red finding and normal red finding classification and segmented candidate microaneurysm areas by applying region growing to image enhanced with morphological top-hat operation and thresholding. The result candidate areas were classified with k-nearest neighbor clustering using the shape and intensity information. use of hemorrhage areas restricted by finite window in training images as input for support vector machine. To detect different sized hemorrhages a pyramid of images was generated by changing the resolution of fundus image. The local minima of the support vector machine provided evidence map were selected as hemorrhage locations. The principal component analysis was used to reduce the complexity of feature space. Some methods sharpened the edges of red finding regions by applying moat operator to green channel of the contrast enhanced image. From the result image, red findings were extracted with recursive region growing and thresholding.

3. METHODOLOGY

The widely available diabetic retinopathy dataset STARE has been used in the evaluation process. There are twenty retinal fundus slides and their ground truth images in the STARE (Structured Analysis of Retina) database comprises 20 eye-fundus color images (ten of them contain pathology) captured with a TopCon TRV-50 fundus camera at 35 FOV. The images were digitalized to 700 × 605 pixels, 8 bits per color channel and are available in PPM format. In the proposed automated system, all images are preprocessed first to eliminate false photographic artifacts and illumination inconsistencies. The preprocessing module proceeds by histogram equalization and contrast enhancement then the next stage is feature extraction followed by classification, Following are the steps taken:

A. Preprocessing

There is a huge variance in contrast, brightness and luminosity inside the retinal images, which make it composite and extort retinal features. Therefore, image pre-processing is fundamentally required to eliminate the occurrence of noise in the image and equalization of the unbalanced illumination present inside the fundus retinal images .The image pre-processing includes the following steps:

1) *HSI color space conversion:* The unique "RGB image" is transformed to "HSI (HUE, SATURATION and INTENSITY) color space." [4] The HSI is the most frequently used color space for image pre-processing applications because it displays the precise color likeness as the human eye senses the color. The lightness, intensity or value is related to the color luminance." [4]

The equations used for the transformation of RGB to HSI are:

Hue component is given by:

$$H = \theta \text{ (if } B > G \text{)}$$

Else

$$360 - \theta \text{ if } B > G$$

Where

$$\theta = \cos^{-1} \left\{ \frac{1}{2} [(R-G) + (R+B)] / \sqrt{[(R-G)^2 + (R-B) - G - B]^2} \right\}$$

Saturation component is given by:

$$S = 1 - \left[\frac{3}{2} (R+G+B) \right] / [\min(R,G,B)]$$

Intensity component is given by:

$$I = 1/3(R+G+B)$$

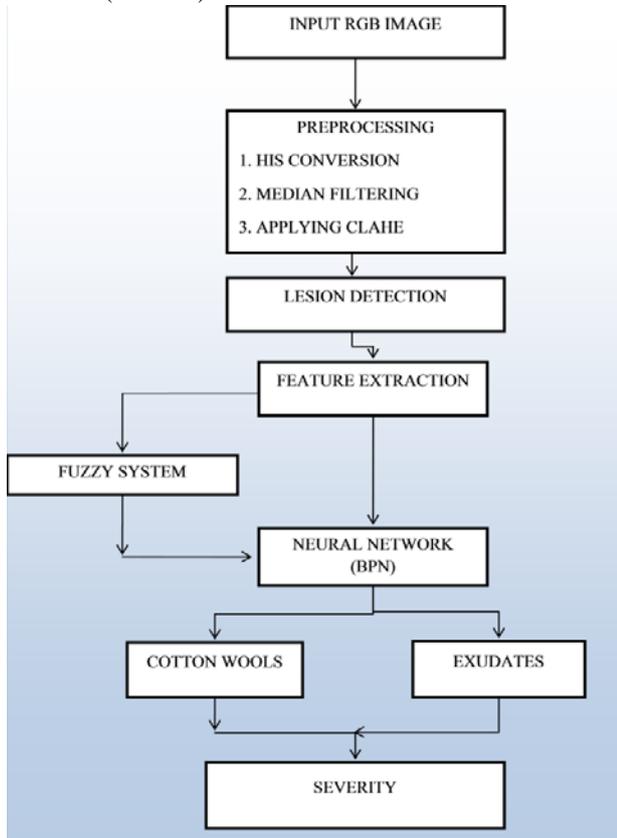


Fig. 1. System Flow showing methodology chosen

2) *Median Filtering*: Median filtering is the best technique for suppressing the secluded noise without distorting sharp edges. It modifies the pixel by the degree of median of all pixels in the surrounding of small sliding window. Median filter helps in eradicating the salt and pepper noise and horizontal perusing artifacts. During the image pre-processing, the salt and pepper noise is added to the intensity band and then it is strained by using median filtering of 3*3 sizes.

3) *Average Filtering*: For a higher specification and more accuracy we further applied the result of median filtering to average filtering in order to get added results, this is done as a further novelty in our work with existing MATLAB function and with newly made function. This do the same work but get the degree of median on average basis.

4) *ADAPTIVE HISTOGRAM EQUALIZATION*

The fundus images typically consists of the rough illumination, the central zone of the image is the brightest part of the image as related to the lateral areas of the image. Hence the brightness of the image reduces as we move away from the center of the image. To get even

illumination, “contrast limited adaptive histogram equalization” is used. With the help of this the darker area of the input image turns out to be the brighter area in the output image. It keeps the uniform illumination in the image. The function *adapthisteq()* is accessible in the MATLAB which is used for put on “Contrast-Limited Adaptive Histogram Equalization” to resultant intensity band.

B. *Detection of Lesions*

Lesions are formed by the leakage of blood vessels. Different lesions have different intensity values of pixel. To identify the lesions, intensity value of pixels is calculated using a dynamic thresholding technique. Manually the threshold value of lesions is calculated for 50 images in database. On the basis of observation of manual thresholding a general mathematical equation is formed to calculate a general threshold value for each image as follows:

$$K = ((\min(M) + \max(M)) / 2) + (\max(M) / 4)$$

$\min(M)$ = minimum intensity value of pixel

$\max(M)$ = maximum intensity value of pixel

If the intensity value of the pixel in the image is less then the threshold value calculated from the general equation, then new value for that pixel value is zero whereas if the intensity value of the pixel in the image is greater than the threshold value calculated from the general equation, then the new pixel value is one.

The resultant image will consist of the lesions in the image.

C. *Features Extraction*

There are number of features that can be extracted to detect the problem which classifies the diabetic retinopathy. The nine features are been extracted from the lesions to fed into a neural network model to classify the problem causing diabetic retinopathy. The following are the features that are extracted:

1) *Geometric Feature (Area, Perimeter, and Compactness)*: Area is the total number of pixels in a particular lesion in a given image. Perimeter can be defined as the total number of pixels at the boundary of the lesion. The feature compactness defines that how closely or compactly the total number of pixels in a lesion are attached or joins. The formula to calculate the compactness of a lesion is $(\text{perimeter} * \text{perimeter}) / 4 * \pi * \text{area}$. Geometric features are required to calculate the shape of a lesion.

2) *Hue Features (Average Hue, Standard Deviation of Hue)*: “The pure color of a lesion is described by a color attribute known as hue.” [4] Average hue and Standard deviation of a hue helps in determining the color of an lesion. The MATLAB function is used to calculate the average hue and standard deviation of hue.

3) *Saturation Features (Average Saturation, Standard Deviation Of Saturation)*: “Saturation gives a measure of

the degree which the amount of white light mixed with the hue. “[4] Average saturation and Standard deviation of a saturation helps in determining the color of a lesion. The MATLAB function is used to calculate the average saturation and standard deviation of saturation.

4) *Intensity Features (Average Intensity, Standard Deviation Of Intensity)*: “The lightness, intensity or value is related to the color luminance.” [4] Average intensity and Standard deviation of a intensity helps in determining the color of an lesion. The MATLAB function is used to calculate the average intensity and standard deviation of intensity.

D. Back Propagation Learning Algorithm

Back propagation is a supervised learning algorithm, every input in a back propagation algorithm requires a desired output so that loss function gradient can be calculated. It maps the set of inputs to the correct outputs.

Back propagation learning algorithm is divided into two sub modules.

Module 1 Propagation: Each propagation has the following steps:

- “Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.” [17]
- Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.
- Module 2 Weight Update For each weight-synapse has the following steps:
- Multiply its output delta and input activation to get the gradient of the weight.
- Subtract a ratio (percentage) of the gradient from the weight.

The back propagation algorithm consists of nine input neurons that are the feature vector formed from the extracted features that are area, perimeter, compactness, average hue, average saturation, and average intensity, standard deviation of hue, standard deviation of saturation and standard deviation of intensity. These feature vectors are normalized before feeding into a neural network into the range of 0-1.

Formula to normalize the features is = (FeatureVal – minVal) / (maxVal – min Val).

Initially weights adjusted are randomly between -1 to 1. It also consists of twenty five hidden neurons with a single hidden layer and two output neurons the output neurons are cotton wools and exudates.

4. SYSTEM ARCHITECTURE :

Technical System architecture is as following:

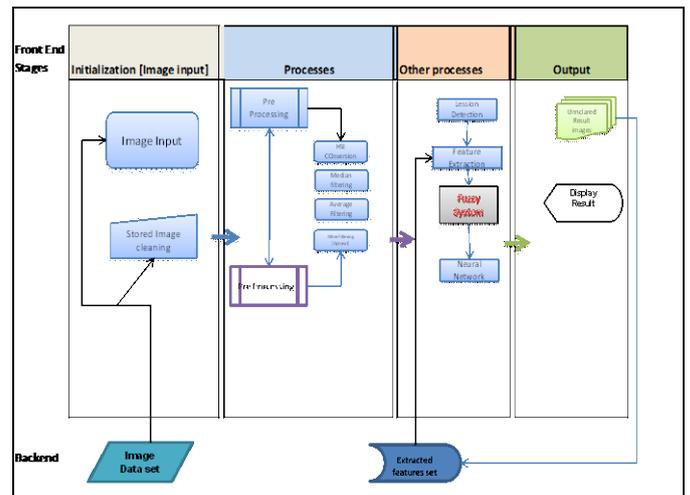


Fig. 2 System Architecture

5. ALGORITHMS USED

While developing of system we are using following algorithm:

Three Stages Algorithm process:

Stage 1: Image acquisition & requirement

Fundus Image s location & correction/Detection

- a) Background contrastation
- b) Foreground modification & vascular extraction with iterative access of next bright part
- c) Foreground candidate region mapping for red lesions

Stage 2: Hierarchal Lesion classification

IF Foreground region for bright lesion repeatedly 1.1 used

Repeatedly classify the regions as per parameters already defined as bright lesion or Non lesion-// if found Bright categorized as Cotton wools {Spot} else Hard exudates

Else IF Foreground region for red lesion

Repeatedly classification of regions as per parameters already defined as Red lesion or Non lesion-// if found Red categorized as Microaneurysms else Hemorrhages

Stage 3: DR Disease Grading result Updated & store result in data set

6. RESULTS

Preprocessing



Fig. 2. Original Image RGB Image

Snapshot of an image after converting RGB image into hue, saturation, intensity image

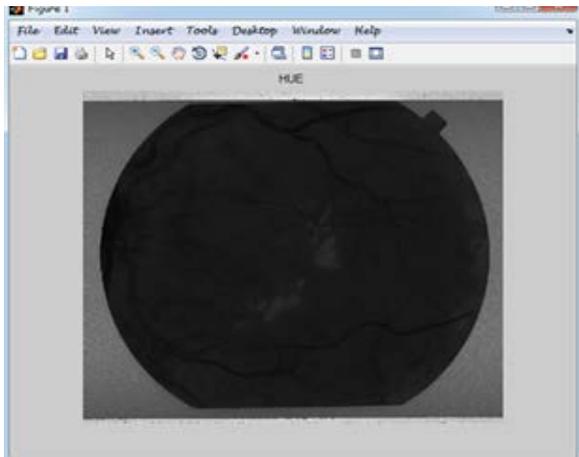


Fig. 3. Hue Image

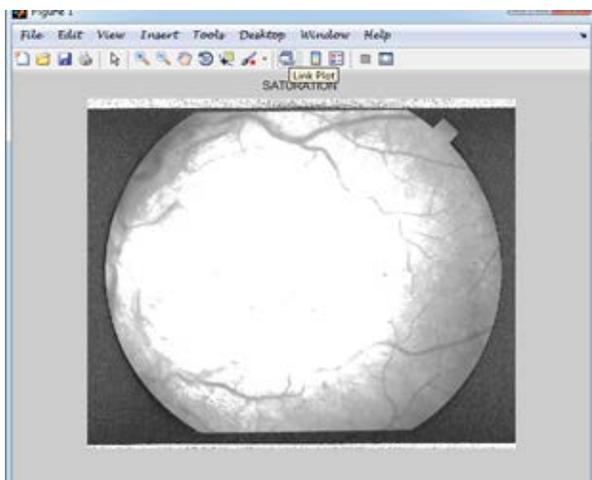


Fig. 4. Saturation Image

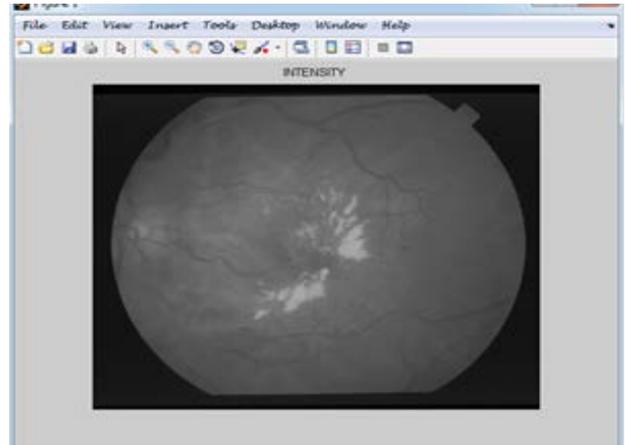


Fig. 5. Intensity Image

Snapshot of an image after applying median & average filtering

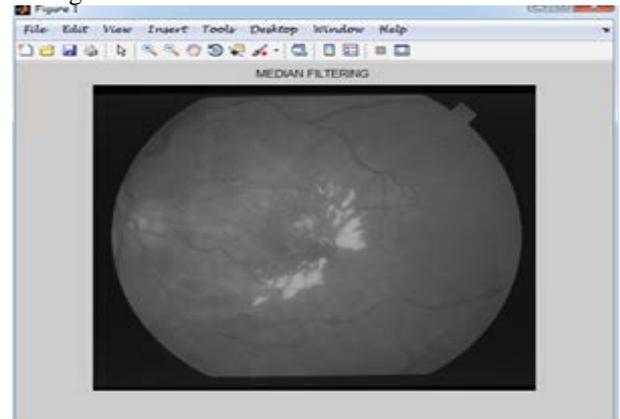


Fig. 6. Average & Median Filtering

Snapshot of an image after applying contrast limited adaptive histogram equalization (CLAHE)

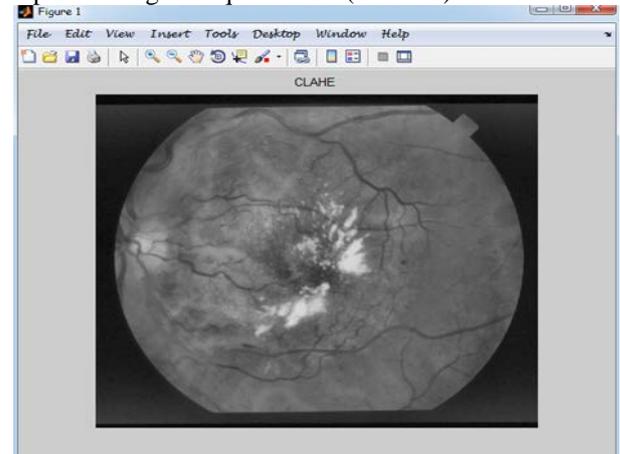


Fig. 7. CLAHE

Snapshot of Lesions Detection

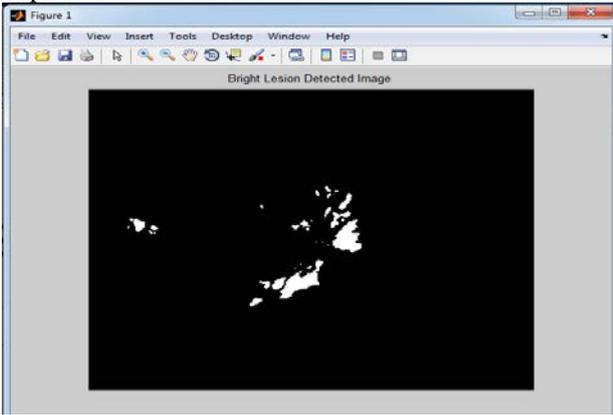


Fig. 8. Lesions Detection

Snapshot of features extraction: 34 Lesions in original RGB image

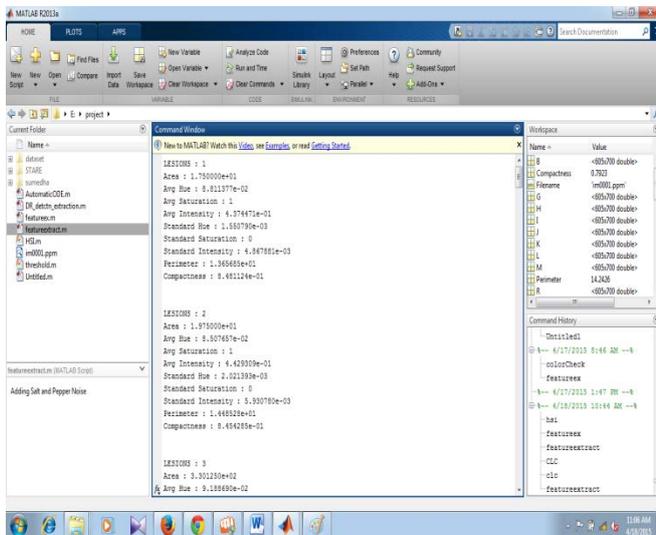


Fig. 9. Features Extracted from Lesion 1 and Lesion 2

Performance of back propagation learning algorithm

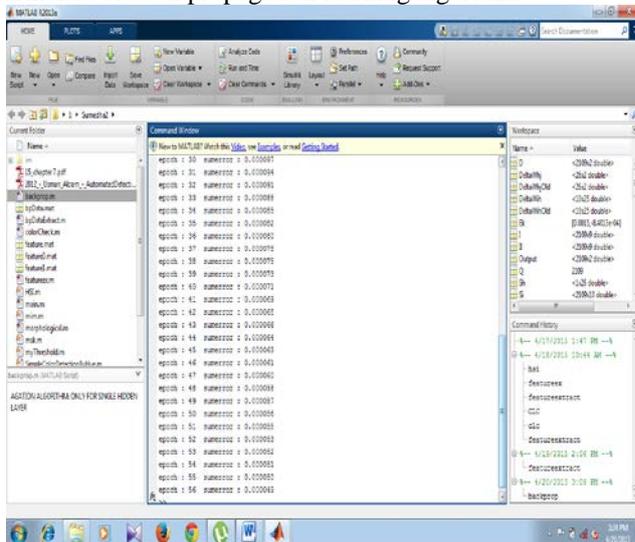


Fig. 10. Epoch Value after reaching meaning error.

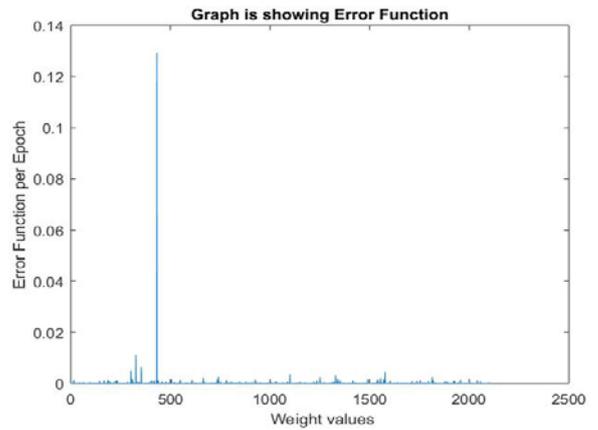


Fig. 11. Error Rate

TABLE I. SHOWING METHOD COMPARISON VALUES

Methods used	Space Complexity	Time Complexity
Fuzzy	1.34E+09	2.959427
Neural Network	1.32E+09	1.772877

As per above table result we are following Neural Network Method as a core method to use in our existing algorithm since it is giving best time space complexity

Fetures Detected	Values
No. of Images used	20
No. of Normal eyes	10
No. of Abnormal eyes	10
No. of Lesion found	34
Total No. of Hard exudates found	27
Total No. of soft exudates/cotton wools found	7
Actual No. of Lesion present in abnormal eyes	35
Actual no. of lesion preset in normal eye	0
Accuracy (%)	97.14%

7. CONCLUSION

This Research Work proposes an automatic detection of Diabetic Retinopathy, which is helpful for ophthalmologists. It detects the bright lesions in the eye

which are the problems of diabetic retinopathy like cotton wools and exudates. Using of neural network (Back propagation learning algorithm) helps in classification between the two problems of diabetic retinopathy (cotton wools and exudates) and detection of the presence of the diabetic retinopathy. Knowing the severity of the problem on the basis of the number of exudates and the cotton wools helps in taking the step earlier for cure of disease. Best performance of BPN was found with Accuracy of 97.14 %

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