Classification and Grading of Diabetic Retinal Images for Implementation of Computer-Aided Diagnosis System

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Abstract—**Diabetes occurs when the pancreas fails to secrete enough insulin, slowly affecting the retina of the human eye. As it progresses, the vision of a patient starts deteriorating, leading to diabetic retinopathy. In this regard, retinal images acquired through fundal camera aid in analyzing the consequences, nature, and status of the effect of diabetes on the eye. The objectives of this study are to (i) image enhancement and denoising using Gabor filter (ii) detect blood vessel and identify the optic disc and vessel parameters and (iii) classify different stages of diabetic retinopathy into mild, moderate, severe non-proliferative diabetic retinopathy (NPDR) and proliferative Diabetic retinopathy (PDR). Computer aided diagnosis system is developed to classify and grading the retinal images using neural network and validated with various samples. Multiple features and BPN classifier is used to enhance the classification of retinal images and is helpful for ophthalmologist in efficient decision making. Classification of the different stages of eye disease was done using Back Propagation Network (BPN) technique based on the area of the exudates, micro aneurysms, and hemorrhages. Accuracy assessment of the classified output is 92.5% for the abnormal cases.**

Keywords- retina, blood vessel, exudates, micro aneurysms, hemorrhages, optic disc, classification, diabetic retinopathy, back propagation network (BPN).

I. INTRODUCTION

Diabetes is a disease which occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. As diabetes progresses, the disease slowly affects the circulatory system including the retina and occurs as a result of long term accumulated damage to the blood vessels, declining the vision of the patient leading to diabetic retinopathy. After 15 years of diabetes about 10% of people become blind and approximately 2% develop severe visual impairment. According to an estimate by WHO, more than 220 million people worldwide have diabetes [1]. It is the sixth largest cause of blindness among the people of working age in India, making it the world's diabetic capital.

Retinal images acquired through fundal camera with back-mounted digital camera [2] provide useful information about the consequence, nature, and status of the effect of diabetes on the eye. These images assist ophthalmologist to evaluate patients in order to plan different forms of management and monitor the progress more efficiently [3]. The retinal microvasculature is unique in that it is the only part of human circulation that can be directly visualised non-invasively in vivo, and can be easily photographed for digital image analysis [2].

In the medical context, the problem arises while making the medical decision when the state of the patient has to be assigned to the initially known class. In most of the cases, the boundaries between the different abnormal classes are not straightforward which further add to the complexity. These classification problems are specific in the case of ophthalmologic applications. In ophthalmology, eye fundus examinations are highly preferred for diagnosing the abnormalities and follow-up of the development of the eye disease. But the problem of diagnosis lies in the huge amount examinations which has to be performed by the specialists to detect the abnormalities. An automated system based on neural computing overcome this problem by identifying automatically all the images with abnormalities [4].

If the disease is detected in its early stages, laser photocoagulation can slow down the progression of DR. However, this is not easy because DR is asymptomatic in these stages. To ensure that treatment is received on time, the eye fundus of diabetic patients needs to be examined at least once a year. Automatic detection of clinical signs of DR can help ophthalmologists in the diagnosis of the disease, with the subsequent cost and time savings [5].

Yun et al., (2008) [3] proposed automatic classification of different stages of diabetic retinopathy - mild non-proliferative retinopathy, moderate non-proliferative retinopathy, severe non-proliferative retinopathy and proliferative retinopathy using neural network from six features extracted from the retinal images.

In this work, we propose a new method of blood vessel extraction which is an improvement over the previously developed matched filter, a new method of hemorrhages detection and classify the retinal cases using an back propagation method with higher classification accuracy. The objectives of this work are: (i) image enhancement and denoising using Gabor filter (ii) detect blood vessel and identify optic disc and vessel parameters and (iii) classify different stages of diabetic retinopathy into mild, moderate, severe non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR).

The work is organized as follows: section II discusses the enhancement using gabor filter, proposed algorithms for blood vessel and optic disc extraction, hemorrhage, exudates, micro aneurysms detection and a brief discussion on the back propagation network classification algorithm. Results of the algorithmic implementation on the data are presented in section III, followed by discussion and conclusions in section IV.

II. MATERIALS AND METHODS

Retinal images of normal, moderate, Severe NPDR, and PDR cases used in this work were downloaded from STARE (Structured Analysis of the Retina) Project database (http://www.parl.clemson.edu/stare/). They were acquired in 24-bits per pixel JPEG format with a dimension of 576 x 768.

A. Image Enhancement and Denoising using Gabor filter

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image.

Gabor filtering can be used for preprocessing to obtain the sharp edges. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually.

Complex,

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (1)$$

Real,

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \psi\right) \quad (2)$$

Imaginary,

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda} + \psi\right) \quad (3)$$

Where,

$$x' = x\cos\theta + y\sin\theta \quad (4)$$

Where,

$$x' = x\cos\theta + y\sin\theta \quad (5)$$

and

$$y' = -x\sin\theta + y\cos\theta \quad (6)$$

In this equation, λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

Histogram equalization is a technique for adjusting image intensities to enhance contrast. Let f be a given image represented as a mr by mc matrix of integer pixel intensities ranging from 0 to $L-1$. L is the number of possible intensity values, often 256. Let p denote the normalized histogram of f with a bin for each possible intensity.

So,

$$p_n = \frac{\text{number of pixels with intensity } n}{\text{total number of pixels}} \qquad n = 0,1,...,L-1. \quad (7)$$

The histogram equalized image g will be defined by,

$$g_{i,j} = \text{floor}\left((L-1)\sum_{n=0}^{f_{i,j}} p_n\right) \quad (8)$$

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness value of the image. AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification. Fig.1 shows the proposed decision support system used for classifying and grading retinal images.
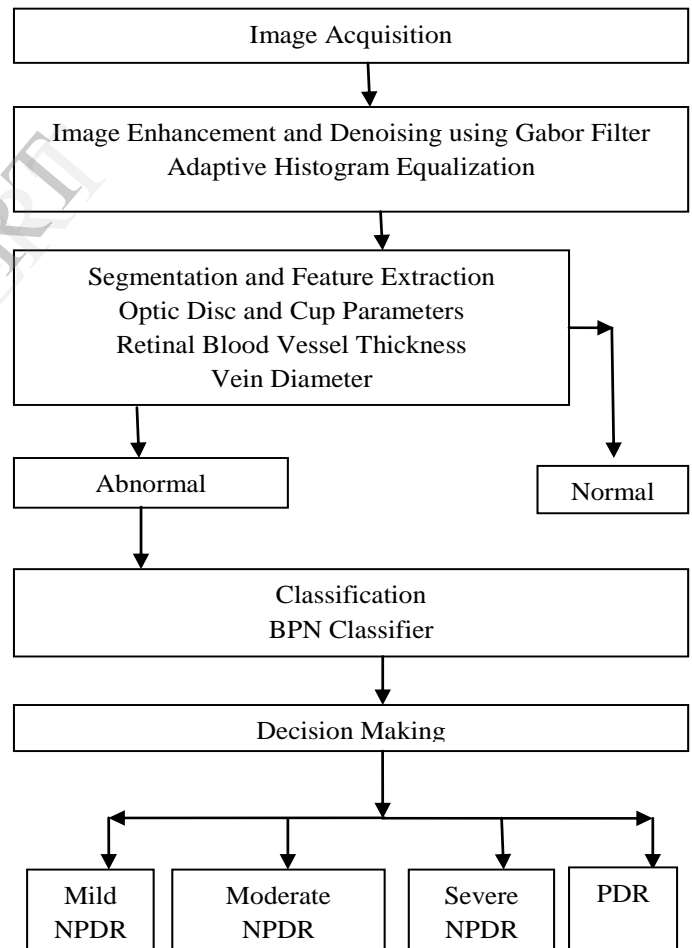
Fig 1: Flow diagram for proposed decision support system for classifying and grading of retinal images

B. Retinal optic disc, blood vessel segmentation and parameter estimation

Image segmentation plays a crucial role in feature extraction process. This work proposes an improved feature segmentation scheme for optic disc segmentation from diabetic retinopathy images and parameter estimation from blood vessel extraction. The mean shift algorithm is a powerful technique for optic disc segmentation [9]. The algorithm recursively moves to the kernel smoothed centroid for every data point using threshold technique.

Proposed method of vessel thickness measurement is made up of three parts: Binarization, Skeletonization, Thickness measurement. Image is binarized to get the blood vessel structure clearly. Skeletonized to get the overall structure of all the terminal and branching nodes of the blood vessels.

Binarization: Mainly used for thickness measurement of the blood vessel, Extract blood vessel structure and shape of the retina image and any small variation occurs in a vessel structure of the retina can be magnified.

Skeletonization: Get the overall structure of all terminal and branching nodes of the blood vessels clearly. Skeletonization is achieved by using erosion and opening. Erosion is converting thick vessel into thin vessel and getting an exact thickness of the vascular network. Erosion followed by dilation is called as opening.

Vessel thickness measurement: Measuring the end points and branching points of extracted blood vessel. End point can be measured by obtaining vessel thickness of branching vessel. Branching point can be measured by obtaining vessel thickness of main vessel (end point and branch points are determined from skeleton image).
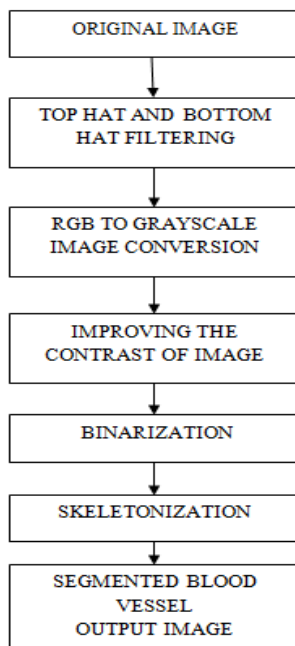

Fig 2: Flow diagram for extracting blood vessel from retinal image

Number t of transitions can be obtained by moving clockwise around from black to white. The eight neighbourhood point is counted can be classified as follows,

t =1; determines a end (terminal) point
t =0, 2; determines a non significant node
t >=3; determines a branching point

Main vessel thickness : Measured by three pixel value before the branching point from that point perpendicular to the skeletal image of the thickness is measured in the binary image.

Branch vessel thickness : Measured by three pixel value before the terminal point from that point perpendicular to the skeletal image of the thickness is measured in the binary image.

Vein Diameter can be obtained by morphological closing and thinning. Morphological closing closes the holes created by noise. Thinning produces the binary image to obtain vein centerlines. Diameters are measured along each centerline branch using the original image. Two basic assumptions have been made: Vein is significantly larger than the diagonal measurement of a pixel and Inner regions of the vein and the background have relatively constant intensities. The vein diameter d can be obtained by,

$$d = \frac{1}{V_{min} - V_{max}}\left(\sum_{i \in R} a_i p_G - p_R V_{max}\right) \quad (9)$$

In this equation, a_i is the gray value of the ith pixel. V*min* and V*max* are the estimated minimum and maximum intensities. P_G is the distance between pixel centers measured. R is the region of width P_R over which the diameter estimate *d* is to be found and let all distance measurements be in units of *P*. The features have been identified from the extracted vessel.

C. Classification

Classification plays a major role in retinal image analysis for detecting the various abnormalities in retinal images [8]. An automatic method to detect various exudates hemorrhages and micro aneurysms associated with diabetic retinopathy facilitates the ophthalmologists in accurate diagnosis and treatment planning. Abnormal retinal images fall into four different classes namely: mild, moderate, severe non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Back Propagation network (BPN) algorithm is used for classifying different stages of diabatic retinopathy.

Back propagation network is the primarily used supervised artificial neural network. Before the training process begins, the selection of architecture plays a vital role in determining the classification accuracy. In this classification scheme, a three layer network is developed in general. An input vector and the corresponding desired output are considered first. The input is propagated forward through the network to compute the output vector. The output vector is compared with the desired output and the errors are determined. The process is repeated until the errors being minimized [4].

The architecture of the back propagation neural network used for the classification system consists of three layers namely input layer, hidden layer and output layer. The input layer and the hidden layer neurons are interconnected by the set of weight vectors U and the hidden layer and the output layer neurons are interconnected by the weight matrix V. In addition to the input vector and output vector, the target vector T is given to the output layer neurons. Since Back Propagation Network operates in the supervised mode, the target vector is mandatory. During the training process, the difference between the output vector and the target vector is calculated and the weight values are updated based on the difference value.

Training algorithm: Training algorithms for feed forward networks use the gradient of the performance function to determine how to adjust the weights to minimize performance. The weight vectors are randomly initialized to trigger the training process. During training, the weights of the network are iteratively adjusted to minimize the network performance function in the sense of sum of squared error:

$$E = \sum (T-Y)^2 \tag{10}$$

Where, T is target vector, Y is output vector. Such a learning algorithm uses the gradient of the performance function with a view to determine how to adjust the weights in order to minimize the error. The gradient is determined using a technique called back propagation, which involves performing computational backwards through the network. Back propagation learning updates the network weights in the direction where the performance function decreases most rapidly, the gradient being negative. Such an iterative process can be expressed as:

$$W_{K+1} = W_k - \alpha \cdot g_k \tag{11}$$

Where, W_k is a weight vector which includes U and V. α is Learning rate and g_k is Current gradient. The gradient vector is the derivative of the error value with respect to the weights. Hence, the weight updation criterion of the BPN network is given by:

$$W_{K+1} = W_k - \alpha \cdot \frac{\partial E}{\partial Wk} \tag{12}$$

Where, k is iteration counter. E is a difference between the target and the output values of the network. When the weight vectors U and V of the network remain constant for successive iterations, then the network is said to be stabilized. These weight vectors are the finalized vectors which represent the trained network. The testing images are then given as input to the trained network and the performance measures are analyzed.

D. Accuracy Assessment

The accuracy of the classification was done using sensitivity, specificity, positive prediction value (PPV), negative prediction value (NPV) as given by equations (13-17) based on the four possible outcomes - true positive (TP), false positive (FP), true negative (TN) and false negative (FN).

$$Sensitivity = TP / (TP + FN) \tag{13}$$

$$Specificity = TN / (FP + TN) \tag{14}$$

$$PPV = TP / (TP + FP) \tag{15}$$

$$NPV = TN / (TN + FN) \tag{16}$$

$$Accuracy = (TP + TN) / (TP + FN + TN + FP) \tag{17}$$

The sensitivity measures the proportion of actual positives which are correctly identified. The specificity measures the proportion of negatives which are correctly identified. PPV and NPV were correctly identified.

III. RESULTS

A. Image Enhancement and denoising using Gabor filter

The images have been obtained from the available data bases STARE (Structured Analysis of the Retina) for developing the decision support system. Then the system is validated considering the real time image obtained. The performance of various levels of the diabetic retinal image have been analyzed and compared by using extracted feature. Image can be denoised using Gabor filter by varying the parameters such as lambda, aspect ratio and theta.
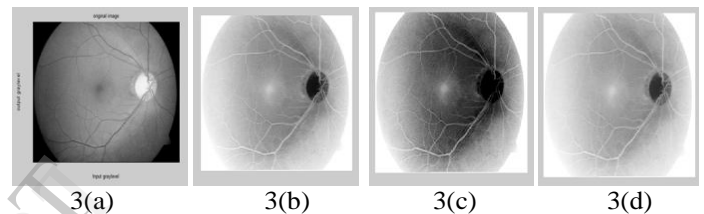

3(a) 3(b) 3(c) 3(d)

Fig 3: Images obtained by varying the theta value using Gabor filter (a) original gray scale image (b) σ = 4,γ = 2,λ = 4,**ө = 0**,ψ = 0 (c) σ = 4,γ = 2,λ = 4,**ө = 45**,ψ = 0 (d) σ = 4,γ = 2,λ = 4,**ө = 135**,ψ = 0.
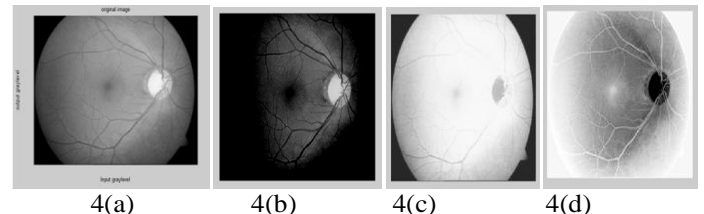

4(a) 4(b) 4(c) 4(d)

Fig 4: Images obtained by varying the aspect ratio value using Gabor filter (a) original gray scale image (b) σ = 4,γ = 2,λ = 4,ө = 45,**ψ = 10** (c) σ = 4,γ = 2,λ = 4,ө = 45,**ψ = 30** (d) σ = 4,γ = 2,λ = 4,ө = 45,**ψ = 50**.
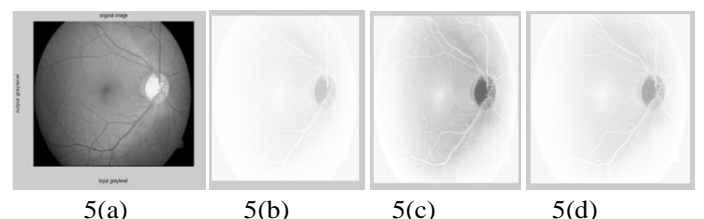

5(a) 5(b) 5(c) 5(d)

Fig 5: Images obtained by varying the lambda value using Gabor filter (a) original gray scale image (b) σ = 4,γ = 2,**λ = 10**,ө = 45,ψ = 50 (c) σ = 4,γ = 2,**λ = 6**,ө = 45,ψ = 50 (d) σ = 4,γ=2,**λ=8**,ө=45,ψ=50.

In the development of automated diabetic retinal image classification system, the analysis of diabetic retina detection depends on the region of interest such as exudates, hemorrhages and micro aneurysms. Hence an image denoising and enhancement is required to preserve the image, highlighting the image feature and suppressing the noise.
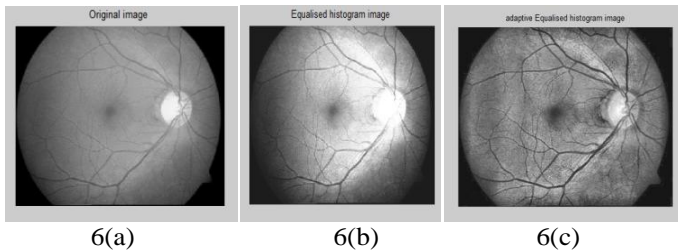

6(a)   6(b)   6(c)

Fig 6: Enhanced Image (a) original gray scale image (b) Equalized histogram processed image (c) Adaptive histogram equalized image.

B. Retinal optic disc, blood vessel segmentation and parameter estimation

Fig 2 shows the flow diagram for extracting the blood vessels and the results obtained for normal and abnormal image have been shown in the fig (7, 8). The output obtained after blood vessel segmentation using top hat, bottom hat filtering have been compared with the results obtained by using local entropy method, spatial filtering using kirsch templates, median filtering and morphological operators. The parameters of the retinal blood vessels were also estimated. Experiments show that the system not only efficiently segments healthy optic discs but also effectively segments out affected optic discs and blood vessels. Features extracted from these segmented images can be used for possible implementation of computer aided automate diagnosis systems for diabetic retinopathy.
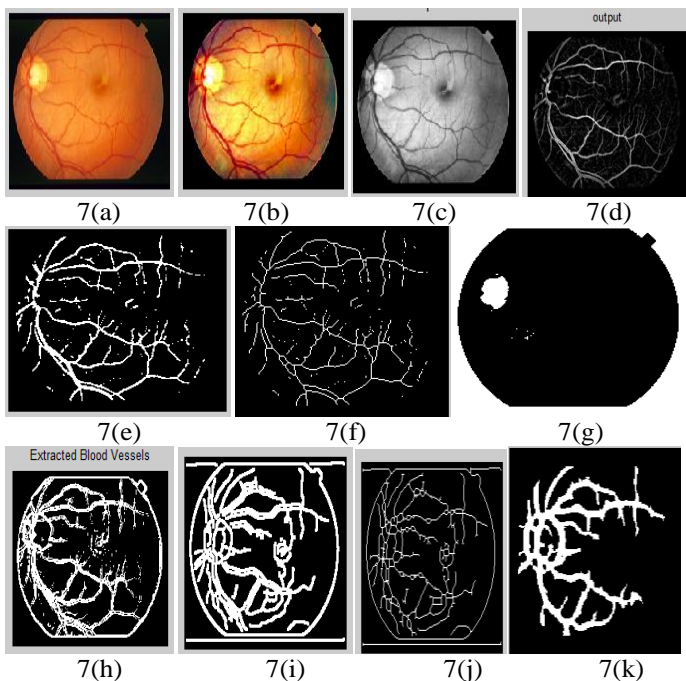

7(a)   7(b)   7(c)   7(d)

7(e)   7(f)   7(g)

7(h)   7(i)   7(j)   7(k)

Fig 7: Segmented results for normal image (a) Input image

(b) Top hat and bottom hat filtered image (c) Gray scale image (d) Contrast improved image (e) Binarized image (f) Skeletonized image (g) Segmented optic disc (h) Extracted blood vessel using spatial filtering with kirsch templates (i) Edge detected binary image using median filtering (j) sketonized image obtained after median filtering (k) Local entropy method.

8(a)   8(b)   8(c)   8(d)
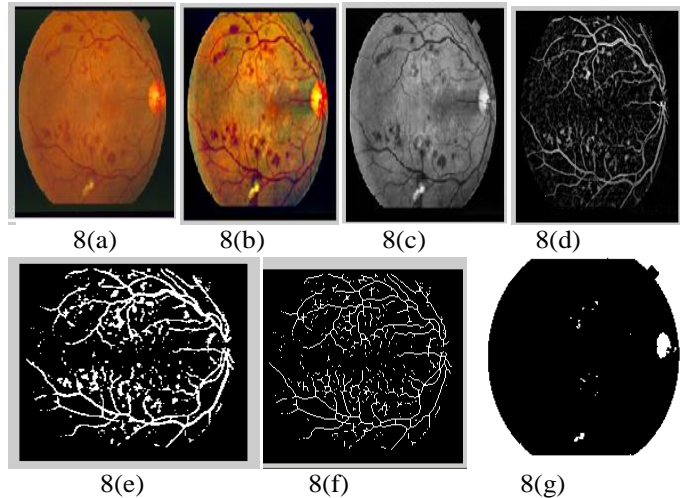
8(e)   8(f)   8(g)

Fig 8: Segmented results for abnormal image (a) Input image (b) Top hat and bottom hat filtered image (c) Gray scale image (d) Contrast improved image (e) Binarized image (f) Skeletonized image (g) Segmented optic disc.

Table 1: Estimation of vessel parameters

Samples	Mean	Standard deviation	Main vessel thickness	Branch vessel thickness
Sample1 (Normal)	2.750	0.667	3.222	2.278
Sample 4 (Abnormal)	2.510	0.652	2.46	1.556
Sample 2 (Normal)	2.839	0.688	3.615	2.242
Sample 5 (Abnormal)	2.466	0.659	2.938	1.637
Sample 3 (Normal)	2.678	0.616	2.64	2.07

The retinal blood vessels parameter like main vessel thickness, standard deviation, mean and branching vessel thickness are calculated using Digimizer and the results have been tabulated in table 1.

C. Classification of different stages of Diabetic Retinopathy

In the present work, the features of the retinal images such as Micro aneurysms, Hemorrhages, exudates have been extracted based on the area of the abnormal retinal images. Computer aided diagnosis system is developed to classify and grading the retinal images using neural network and validated with various samples. Multiple features and BPN classifier is used to enhance the classification of retinal images and is helpful for ophthalmologist in efficient decision making. The parameters such as area, entropy, energy, co-variance, standard deviation and elapsed time for each retinal images have been calculated and the various stages of diabetic retinopathy have been identified.

9(a)   9(b)   9(c)
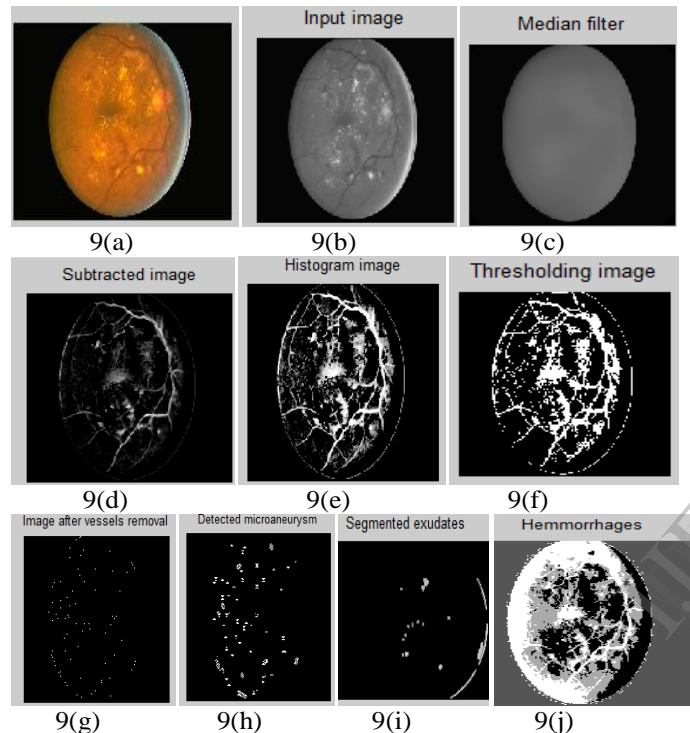9(d)   9(e)   9(f)
9(g)   9(h)   9(i)   9(j)

Fig 9: Process of extracting features (a) Input RGB image (b) Gray scale image (c) Median filter (d) Subtracted image (e) Histogram image (f) Thresholding image (g) Image after vessel removal (h) Detected micro aneurysms (i) Segmented exudates (j) Detected Hemorrhages.

The extracted features have been taken for training stage and then the area of hemorrhages, exudates and micro aneurysms have been found and it is helpful for finding the different stages of diabetic retinopathy using a neural network algorithm called Back propagation network (BPN) algorithm.

For the purpose of training and testing the classifiers, the 120 retinal images were divided into two sets – a training set of 50 arbitrary samples and a test set of 70 samples. Table 2 gives detail of the parameters extracted is used for training and test data used for classification. Table 3 provides details about the area of micro aneurysms, hemorrhages and exudates present in the retina and that is used for the identification of diabetic retinopathy stages.

Table 2: Extracted parameters used for training data set

Image	Energy	Elapsed time	Covariance	Standard deviation	Data
Image 1	100	5.000 s	3.7716	13.7233	4.1593;0.1631;1;0; 0.1372;0.0377;4.1593
Image 2	100	5.619 s	10.9292	11.353	3.6922;0.1448;1;0; 0.1137;0.1093;3.6922
Image 3	100	8.754 s	6.3913	11.7555	3.8551;0.1512;1;0; 0.1176;0.0639;3.8551
Image 4	100	5.791 s	11.6507	14.1344	3.6890;0.1447;1;0; 0.1413;0.1165;3.6890
Image 5	100	5.829 s	16.1063	12.5092	3.485;0.1367;1;0; 0.1251;0.111;3.4856
Image 6	100	6.041 s	11.8597	14.4859	3.7473;0.1470;1;0; 0.1449;0.1186;3.7473
Image 7	100	6.449 s	4.7111	10.2059	3.9123;0.1534;1;0; 0.1021;0.0471;3.9123

Table 3: Results obtained using BPN classifier

Images	Microneurysms	Exudates	Hemmorhages	Type
Image 1	584	666241	89495	Mild NPDR
Image 2	370	966105	94808	Moderate NPDR
Image 3	488	76724	99348	Severe NPDR
Image 4	473	691849	102819	PDR
Image 5	522	2327313	103073	Moderate NPDR
Image 6	288	830689	103135	Severe NPDR
Image 7	445	1181004	101422	Mild NPDR

IV. DISCUSSION AND CONCLUSION

The analysis revealed that TP=70, FP=4, TN=41, FN=5, sensitivity=0.93, specificity=0.91, positive predicted value (PPV)=0.945, and negative predicted value (NPV)=0.8913. The overall classification accuracy is 92.5%. This can be shown in the table (4 , 5).

Table 4: Detection results of diseased retinal images

classifier	Number of test images	True positive	True negative	False positive	False negative
BPNN	120	70	41	4	5

Table 5: Performance evaluation of BPN classifier

Sensitivity	93.3%
Specificity	91.1%
Accuracy	92.5%
Positive prediction value(PPV)	0.945
Negative prediction value(NPV)	0.891

This project proposes an improved feature enhancement and segmentation scheme for optic disc and retinal blood vessel segmentation from retinal images. The parameters of the retinal blood vessels were also estimated. Experiments show that the system not only efficiently segments healthy optic discs but also effectively segments out affected optic discs and blood vessels.

Features extracted from these segmented images can be used for possible implementation of computer aided automatic diagnosis systems for diabetic retinopathy. The BPN (Back Propagation Network) classifier is used for retinopathy classification and that can be compared with that of the other classifiers. This cumulative computer aided diagnosis development provides the ophthalmologist to make their decision effectively.

The computer aided diagnostic system to classify the retinal Images using retinal network and BPN classifier has been developed and validated with various samples. The proposed method is capable of detecting the diabetic retinopathy stages sharply with an average accuracy of 92.5%. The experimental result shows that the proposed method yields better sensitivity, specificity, accuracy and predictive values compared to other methods. The classification results obtained by the proposed method are also comparable to those obtained by other methods. The major strengths of the proposed system are accurate feature extractions and accurate grading of non proliferative diabetic retinopathy lesions. Hence the proposed system gives more accurate classification and grading of retinal images. The proposed system can be helpful to detect non proliferative diabetic retinopathy and proliferative diabetic retinopathy lesions in the retinal images to facilitate the ophthalmologists when they diagnose the retinal images.

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