Image Analysis Technique for Detecting Diapetic Retinopathy

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ABSTRACT
Diabetic Retinopathy is an eye disease, DR is the leading cause of the blindness in the working age population. If the disease is detected early and treated promptly many of the visual loss can be prevented. DR occurs in one of the two types,1.Non-proliferative Diabetic Retinopathy(NPDR), 2.Proliferative Diabetic Retinopathy(PDR).This paper describes the development of an automatic fundus image processing and analytic system to facilitate diagonosis of the opthalmologis. Detection of DR disease is done using Radial Basis Function Neural Network (RBFNN) method and the two types are classified and diagnosed successfully. The accuracy of the proposed system is 76.25%.

General Terms
Radial Basis Neural Network classifier, exudates disease

Keywords
Diabetic Retinopathy, Radial Basis Function Neural Network, Blood Vessels, Accuracy.

1. INTRODUCTION
Diabetes is a group of metabolic diseases in which a person has high blood sugar, either because the body does not produce enough insulin, or because cells do not respond to the insulin that is produced. [1] Diabetic retinopathy is one of the common complications of diabetes. It is a severe and widely spread eye disease. It damages the small blood vessels in the retina resulting in loss of vision. [2]Nonproliferative diabetic retinopathy is an early stage of diabetic retinopathy. In this stage, tiny blood vessels within the retina leak blood or fluid. The leaking fluid causes the retina to swell or to form deposits called exudates. Proliferative diabetic retinopathy, PDR is an attempt by the eye to grow or re-supply the retina with new blood vessels (neovascularization), due to widespread closure of the retinal blood supply. [3] Unfortunately, the new, abnormal blood vessels do not re-supply the retina with normal blood flow, but bleed easily and are often accompanied by scar tissue that may wrinkle or detach the retina. In this paper, an automated approach for classification of the disease diabetic retinopathy using fundus images is presented.

The retinal image is taken in the RGB form by fundus camera. A fundus camera or retinal camera is a specialized low power microscope with an attached camera designed to photograph the interior surface of the eye, including the retina, optic disc, macula, and posterior pole. [3]The acquired image resolution is 1280 x 1024 in 24bit JPEG format. The evaluation of the proposed automated diagnosis system of diabetic retinopathy have been performed by using a set of 250 fundus images which is a combination of normal, NPDR and PDR affected images. The original image is converted to gray scale image. After that, adaptive histogram equalization is applied to improve the contrast of the image. Then, Discrete Wavelet Transform(DWT) is applied and the size of the image is reduced into half as 640×512 [4] .[5] Next Matched filter response (MFR) is applied to enhance the blood vessel network. Finally, Fuzzy c-means clustering is applied to segment the blood vessels in the image.

2. PROPOSED SYSTEM
Figure1 block diagram of the proposed system for the diagnosis of DR.

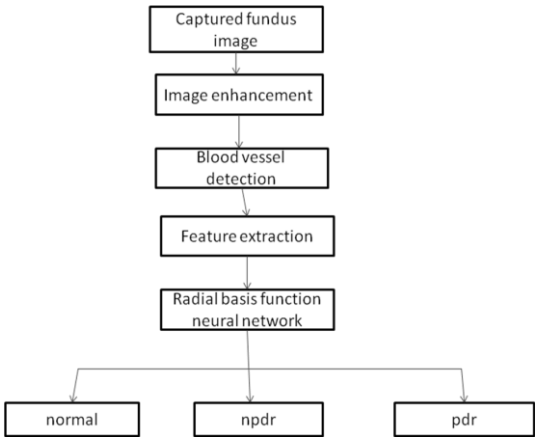


Fig. 1: Block diagram of the proposed system for the diagnosis of DR

I.IMAGE ENHANCEMENT
Image Enhancement improves the quality of the images for human viewing. The purpose of image enhancement is to remove blurring and noise, increasing contrast for the reliable extraction of features since the abnormalities in feature extraction will produce poor results in the noisy background. Steps for image enhancement:

a. The color retinal image is taken as an input image.

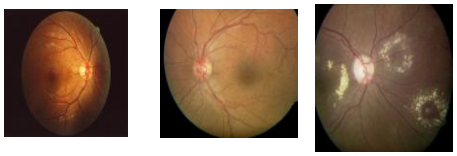
b. The grey scale image is extracted from the input image.

c.After grey scale conversion, adaptive histogram equalization is used to enhance the contrast and improve the quality of the retinal image.

d. Finally morphological technique is applied to remove the noise from the DR images.

a. Input Retinal Image

A combination of normal and DR affected images are taken for enhancement. The size of the input retinal images is 1500×1000 pixels. It can be enhanced with the help of the following steps. Fig. 2 shows the input retinal image of normal and affected DR images.

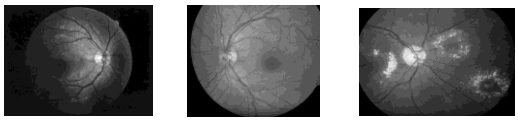


(a) (b) (c)

Fig. 2: Input retinal image for (a)normal, (b)NPDR and (c)PDR

b. Grey Scale Extraction

The retinal image is taken in the RGB form by the fundus camera. A fundus camera or retinal camera is a specialized low power microscope with an attached camera designed to photograph the interior surface of the eye, including the retina, optic disc,posterior pole.



(a) (b) (c)

Fig. 3: Grey scale converted image for (a)normal, (b)NPDR and (c)PDR

The grey scale channel of the RGB space is extracted and chosen for detection of blood vessels because blood vessels appear most contrasted in this channel. Fig. 3 shows the results of green channel extracted image for normal and affected DR images.

c. Adaptive Histogram Equalization

Adaptive histogram equalisation which is used to improve contrast in images, is applied to the gray scale converted eye image. Consider a running sub image W of N × N pixels centered on a pixel P(i,j), the image is filtered to produce another sub image P of (N × N) pixels according to the equation below:

$$P_n = 255\left(\frac{[\phi_w(p)-\phi_w(Min)]}{[\phi_w(Max)-\phi_w(Min)]}\right) \quad (1)$$

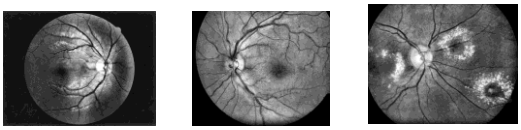
$$\phi_w(P) = \left[1+\exp\left(\frac{\mu_w - p}{\sigma_w}\right)\right]^{-1} \quad (2)$$

and *Max* and *Min* are the maximum and minimum intensity values in the whole eye image, while μ_w indicate the local window mean and σ_w indicate standard deviation which are defined as:

$$\mu_w = \frac{1}{N^2}\Sigma(i,j)\varepsilon(k,l)P(i,j) \quad (3)$$

$$\sigma_w = \sqrt{\frac{1}{N^2}\Sigma_{(i,j)\varepsilon(k,l)}(P(i,j)-\mu_w)^2} \quad (4)$$

The results of eye images after applying Adaptive Histogram Equalization are shown in Fig. 4.



(a) (b) (c)

Fig. 4: Adaptive histogram equalized image for (a)normal, (b)npdr and (c)pdr

II.BLOOD VESSEL DETECTION

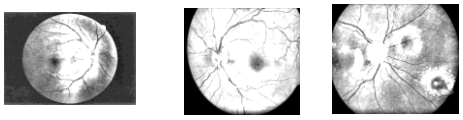
The purpose of locating anatomic structure is to detect the blood vessel based on segmentation of vascular arcades. Detection of the anatomic structure is the characterization of the normal or disease state that exist in the retina.

a. Discrete wavelet transform

The transform of a signal is just another form of representing the signal. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet ψ(t) called mother wavelet by dilations and shifting:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

where ‘a’ is the scaling parameter and ‘b’ is the shifting parameter. The results of eye images after applying Discrete Wavelet Transform are shown in Fig. 6.



(a) (b) (c)

Fig. 5: Discrete wavelet transformed image for (a)normal, (b)NPDR and (c)PDR

b.The matched filter Response

The matched filter is the optimal linear filter for maximizing the signal to noise ratio (SNR) in the presence of additive stochastic noise. The optimal filter is given by

$$h_{opt}(d) = -\exp(-d^2/2\sigma^2)$$

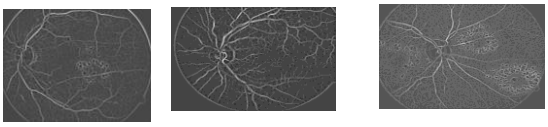
where d is the perpendicular distance between the point (x,y) and the straight line passing through the centre of the blood vessel in a direction along its length and σ defines the

spread of the intensity profile,

The negative sign indicates that the vessels are darker than the background. Also, instead of 'n' different types of objects having to be identified, the problem reduces to deciding whether or not a particular pixel belongs to a blood vessel. Instead of matching a single intensity profile of the cross section of a vessel, a significant improvement can be achieved by matching a number of cross sections (of identical profile) along its length simultaneously. Such a kernel may be mathematically expressed as

$K(x,y) = -\exp(-x^2/2\sigma^2)$ for $|y| \le L/2$

where L is the length of the vessel segment that has the same orientation, σ defines the spread of the intensity profile. Here we have taken L = 7 and σ =2.The values are chosen heuristically. The intensity profile has a Gaussian shape. To be able to detect vessels on all possible orientations, the kernel must be rotated to all possible vessel orientations and the maximum response from the filter bank is registered. As a result of applying this MFR to retinal images, response due to the noise is suppressed significantly, where no blood vessel is present.



(a) (b) (c)

Fig. 6: matched filter image for(a)normal(b)NPDR and (c)PDR

c. The Fuzzy c-means Segmentation

Fuzzy c-means (FCM) Segmentation is a method of clustering which allows one piece of data to belong to two or more clusters. Here it is used to segment the input eye image and detect the blood vessels. Information about blood vessels can be used in grading disease severity or as part of the process of automated diagnosis of diseases with ocular manifestations. It is based on minimization of the following objective function:

$$J_m = \sum_{i-1}^{N}\sum_{j-1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 , 1 \le m < \alpha$$

(8)

where m is the fuzzy co-efficient , any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. The algorithm is composed of the following steps [36]:

1. Initialize U=[u_{ij}] matrix, U(0)

2. At k-step: calculate the centers vectors C(k) = [c_j] with U(k)

$$c_j = \frac{\sum_{i-1}^{N} u_{ij}^m \cdot x_i}{\sum_{i-1}^{N} u_{ij}^m}$$

3. Update U(k) , U(k+1)

$$u_{ij} = \frac{1}{\sum_{k-1}^{c} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}}$$

4. If || U(k+1) – U(k)||<ε then STOP; otherwise return to step 2.

Here we have taken m = 2 and ε = 0.3. The resulting images after applying Fuzzy C-means Segmentation are shown in Fig.7

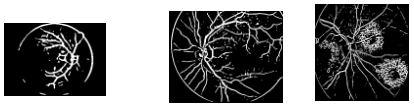


Fig 7:fuzzy c-means segmentation image for(a)normal(b)NPDR(c)PDR

III. FEATURE EXTRACTION

After applying the image enhancing techniques like histogram equalization and noise removal, we obtain a better contrast image. Features like area, radius, diameter, perimeter, center angle,arclength,radian,halfarea,length,sectorarea,sectorperimeter,mean,median,standarddeviation,varience,skewness and average are extracted for detecting the disease. Some of the features that are extracted for detecting diseases are given along with their formula:

1) Area

The area of a circle is the space contained within the circumference and is measured in square units.

$A = \Pi r^2$

2) Radius

The Radius is the distance from the center of the circle to the circumference.

$$\frac{\sqrt{A}}{\Pi}$$

3) Diameter

The Diameter of a circle is the distance from one point of the circumference through the center to the

opposite side of the circle. The diameter is twice the length of the radius.

d = 2* radius

4) Perimeter

The perimeter of a circle is the circular line that marks the limits of a circle.

$$p = 2 * \Pi * \text{radius}$$

5) Centre angle

The angle subtended at the center of a circle by two given points on the circle.

$$ca = \frac{\text{perimeter}^2}{360}$$

6) Arc length

The distance along the curved line making up the arc.

$$arc = \frac{(\text{radius}) * (2 * \Pi * ca)}{360}$$

7) Mins of arc

A minute of arc or minute arc (MOA), is a unit of angular measurement equal to one sixtieth ($^1/_{60}$) of one degree ($^{circle}/_{21,600}$), or ($^{\pi}/_{10,800}$) radians.

Mins of arc= hour angle * 15

8) Volume

The amount o space that something contains or fill is volume.

$$V = \frac{4 * (\Pi * r^3)}{3}$$

.

9) Mean

The mean (also known as average), is obtained by dividing the sum of observed values by the number of observations, *n*.

$$m = \frac{x}{y}$$

where, x= sum of items

y= total no of items

10) Median

The median is the middle value of a set of data containing an odd number of values, or the average of the two middle values of a set of data with an even number of values.

11) Variance

The variance is a measure of how far each value in the data set is from the mean.

$$\delta = \frac{x}{y}$$

where, x=(sum-mean)

y= (sum-mean) ²

12) Standard Deviation

On average, how much each measurement deviates from the mean is called as standard deviation.

$$\sigma = \sqrt{\text{variance}}$$

13) Skewness

Skewness describes the shape of your data set's distribution. Skewness indicates how symmetrical the data set is.

$$\text{Skewness} = \frac{(\text{mean- median})}{\text{standard deviation}}$$

IV CLASSIFICATION OF THE DISEASE USING RBFNN

A radial basis function network is an artificial neural network that uses radial basis functions as an activation functions. It is a linear combination of radial basis functions. Radial Basis Function (RBF) are feed forward networks consisting of three layers, 1.Input Layer 2.Hidden Layer and 3.Output Layer. Fig. 8 shows the architecture of RBFNN.

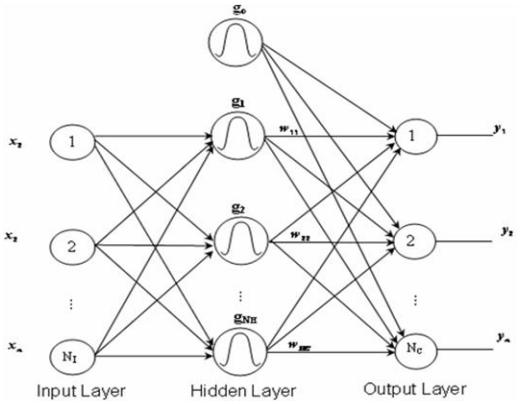


Fig. 8: Architecture of RBFNN

Input Layer: An input vector xn where n varies from 1 to 13 feature values, which is used as an input to all radial basis functions.

Hidden Layer: The hidden layer performs non-linear transformation, where each hidden unit implements a radial activated function. RBF networks are universal approximators.

Output Layer: The output layer consists of three classes y1, y2 and y3 corresponding to three categories of DR images namely normal, npdr and wet. The model has been trained with 200 input images and tested with 63 images.

3. EXPERIMENTAL RESULTS

The performance measure of RBFNN classification are shown in Table 1. The sensitivity and specificity of the proposed system are 65.7% and 84.4% respectively. The accuracy of the proposed system is 76.25%. Table 2 shows the percentage of accuracy of the test data.

Table 1: Performance measure of RBFNN Classification

True Positive	False Positive	True Negative	False Negative
38	**12**	**24**	**7**

Table 2: Percentage of accuracy

Sensitivity	Specificity	Accuracy
65.71%	**84.4%**	**76.25%**

Fig. 9 shows the ROC curve for the system.

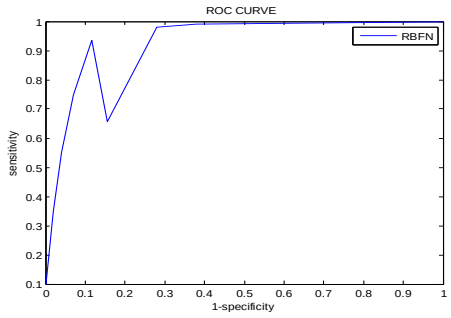


Fig. 9: ROC curve

4. CONCLUSION

Diabetic Retinopathy is a disease which causes vision loss rapidly. As an achievement of this work, the DR has been classified into two categories NPDR and PDR . To the input color retinal images, pre-processing techniques like Grayscale conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, Matched filter Response and Fuzzy C-means segmentation are applied. After applying these pre-processing techniques the quality of the images are improved. From the pre-processed images features were extracted for classification process. Next the features are extracted from the Blood vessel detected images. Finally, the normal, npdr and pdr types are classified with the help of Radial Basis Function Neural Network. This method may be enhanced by taking some more features and by combining with other pattern classification models.

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