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Automated diabetic retinopathy detection using radial basis function

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Abstract

Diabetic mellitus is a major reason of visual impairment an around the world. Early automatic diagnosis of diabetic retinopathy (DR) may avoid vision loss and blindness. The goal of this paper is to automatically detect retinal image as Non DR or DR based on radial basis function (RBF) neural network classifier. This experiment address to explore ophthalmic features such as blood vessels, exudates & microaneurysms and it's segmented from retinal background using A-IFS histon based segmentation method. This obtained feature set delivers to train RBF neural network. The Receiver operation characteristics (ROC) curve is plotted based on evaluated result. The projected experiment has been done on 130 DIARETDB0 & 89 DIARETDB1 retinal images database by using RBF neural network. The experiment perceive the accuracy of 71.2%, Sensitivity 0.83 & Specificity 0.043 for DIARETDB0 and the accuracy of 89.4% Sensitivity 0.94 & Specificity 0.16 for DIARETDB1.

Keywords: Blood Vessels, Diabetic retinopathy, Exudates, Microaneurysms, Tortuosity, RBFNN, Retinal fundus images

1. Introduction

Diabetic is foremost syndrome affecting retinal blood vessels. The rise in blood sugar damage the retinal blood vessels and may leak blood leads to progressive vision loss. There is possibility to control disease if detected in its early stages. Generally in the cases (patients) diabetes mellitus grows 50, 70 and 90% after 10, 20 and 30 Yr

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respectively. According to International Diabetes Federation (IDF) and World Health Organization (WHO), it is noted that about 347 million people worldwide have diabetes. This paper focus on detection of early diabetic retinopathy by some clinical signs in retinal images (fundus images). Diabetic retinopathy (DR) can be mainly classified into proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR). PDR is considered to be the advanced type of retinopathy disease. NPDR is the premature stage retinopathy. DR clinical sign are Blood vessel, Microaneurysms (MA), Exudates and hemorrhages. In the presence of these ophthalmic features NPDR is stratify into mild, moderate and severe as shown in table 1[1][2].

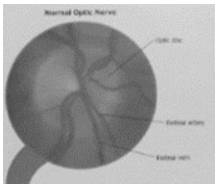
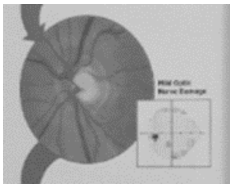
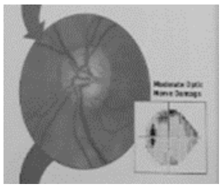
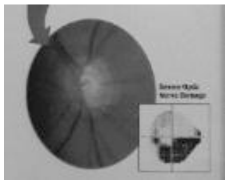
Earlier researchers stated that worldwide there are half of 205,000 ophthalmologists available in six countries which are China, USA, Russia, Japan, Brazil and India [15]. According to previous research there is less than 1 ophthalmologist in 23 countries, less than 4 ophthalmologist in 30 countries, less than 25 ophthalmologist in 48 countries and more than 100 ophthalmologists in 18 countries for apiece million people [15].

As DR is progressive eye ailment which may cause vision loss if it not diagnosis. Particularly in rural areas there is lack of ophthalmologists and examination fees is too high. In this situation proposed system can save the time of ophthalmologists as well as it can be affordable for patient too. The number of ophthalmologist is much lower than the growth of diabetic patient for this reason this work focus on early diabetic retinopathy.

The proposed system contributes in following steps: preprocessing, image enhancement, ROI extraction, ophthalmic features (blood vessels, exudates & microaneurysms). After detecting of ophthalmic features fundus image was determined by system it is DR or Non DR.

This paper organized as follows. Section 2 gives literature review of related work. Section 3 deals with system architecture, image database, preprocessing, feature extraction and RBF. The section 4 presents the result of our propose system. Finally section 5 concludes the paper.

Table 1. NPDR classification and their features.

Normal	Mild	Moderate	Severe
			
	At least single intraretinal haemorrhage or microaneurysm. Hard & soft excudate might be exist or not exist.	In 2 or 3 quadrants intraretinal haemorrhages / Microaneurysm. Presence of Exudates might be or might not be	In 4 quadrants intraretinal haemorrhages/ microaneurysms. Vein beading with 2 quadrants

Features: Microaneurysms appears adjacent tiny blood vessels of macular area. Microaneurysms have greater than 125µm in size and appear as red spot. Hard excudates were yellowish white waxy-appearing spots are arranged in clumps or in circinate way. Presence of small whitish fluffy superficial lesions known as Cotton wool spots / soft excudates. IRMA (Intraretinal microvascular abnormalities) look to be asymmetrical red kines connecting arterioles-venules shunt. Oedema describe retinal thickening is because of capillary leakage.

2. Literature Review

Maria Garcia et al. [3] developed; a system to detect hard exudate from retinal images using radial base function; experimental work has been done using a total of 117 retinal images provided by the IOBA of the Spain, University of Valladolid. Exudate were consequently detected by segmentation algorithm and provides features to radial base Function Neural Network classifier. Mean sensitivity of 92.1% was obtained by utilizing a lesion-based criterion (pixel resolution). And mean specificity of 70.4% was obtained by image based criterion.

M. Garcia et al. [4] studied; RBF Classifier utilization to recognized red lesion in retinal images. Author work on 115 retinal images from the database of IOBA of the Spain, University of Valladolid. Clinical feature i.e. red lesion means hemorrhages and Microaneurysms were extracted and these Feature Vectors were classify using radial base Function Neural Network. The mean sensitivity of 86.0% was achieved for lesion based criterion and mean specificity 56.0% achieved for image based criterion.

Ramalingaswamy Cheruku et al. [5] work on; Diabetes Classification using Radial Basis Function Network by Combining Cluster Validity Index and BAT Optimization with Novel Fitness Function. In this experimental analysis employed on Pima Indians Diabetes (PID) dataset. Estimations of proposed system done with different validity indices i.e. Conventional RBFN, RBFN + Ratio Index, RBFN + DunnIndex, RBFN + DVIndex achived of Accuracy (%) 68.53, 70.00, 69.33, 69.56 respectively.

R. Vijayamadheswaran et al. [6] has experimented on Radial Base Function for DR using color fundus image obtained from Arvind Hospital, Madurai (India). The retinal image process by normalizing, histogram equalization, segmentation and ROI (exudate) was segmented. Features were extracted by contextual clustering (CC) segmentation methods. RBF classifier train to classify image experiment archives 96% accuracy rate.

J.Anitha et al. [7] developed RBFNN methodology for diabetic retinopathy and perform experiment on 275 fundus images dataset acquire from Aravind Eye Hospital, Coimbatore, India. Extracting retinal blood vessels which vary in size and shape. Extracted clinical features provides to RBFNN classifier and archives Sensitivity 96.42%; Specificity 92.4% and Accuracy 93.65%. Author observed from the result that RBF NN is important than Bayesian classifier for diabetic retinopathy.

P. Venkatesanet et al. [8] has worked on 1200 individuals' diabetic dataset collecting from a private hospital during 1996/98. Author used Multilayer Perceptron (MLP) and RBF to classify images with the help of ophthalmic feature. MLP record the Sensitivity 92.1% and specificity 91.1% whereas Radial Basis Function NN achieves Sensitivity of 97.3% & specificity of 96.8%. RBFNN execution time is minimum than MLP but as compared logistic regression RBFNN take somewhat maximum time.

M. Tamil Nidhi et al. [16] studied on Efficient Ranking of Diabetic Retinopathy and Glaucoma Using Echo State Neural Network and Radial Basis Function (RBF). Canny Edge Detector methodology is used for extracting Features like blood vessel. Extracted features were classified using Echo State Neural Network (ESNN) and Radial Basis Function (RBF) and the result obtained by using RBF is increased as compared to Echo State Neural Network (ESNN).

Mohamed Chetoui et al. [17] work on Machine Learning and Texture Features for diabetic retinopathy. Experimental analysis performed on MESSIDOR dataset. Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH) techniques were used to extract exudates, hemorrhages and microaneurysms features. Performance of LESH technique is better than LTP. The SVM with a Radial Basis Function kernel (SVMRBF) achieved 0.904 for LESH technique and accuracy 0.841 for LTP.

3. System Architecture

Structural outline of proposed system i.e. prior diabetic retinopathy system using RBF shown in fig 1. which includes image dataset in order to the extract feature set, and at last feature classification to detect retinal fundus image as DR or No DR/Non DR.

3.1. Image Database

Database DIARETDB0 and DIARETDB1 with 130 and 89 images respectively examined in this experimental work to detect early diabetic retinopathy. Database DIARETDB0 & DIARETDB1 gets easily accessible by a site www.it.lut.fi/project/imageret [9].

3.2. Feature Extraction

Features that helps in experiment to understand and distinguish them from other characteristics in retinal images. The experimental work concentrate on extracting Ophthalmic/clinical feature like exudate, blood vessels, &

microaneurysms. Features having erraticism within retinal image texture in a clinical environment. Feature extraction starts with preprocessing the image.

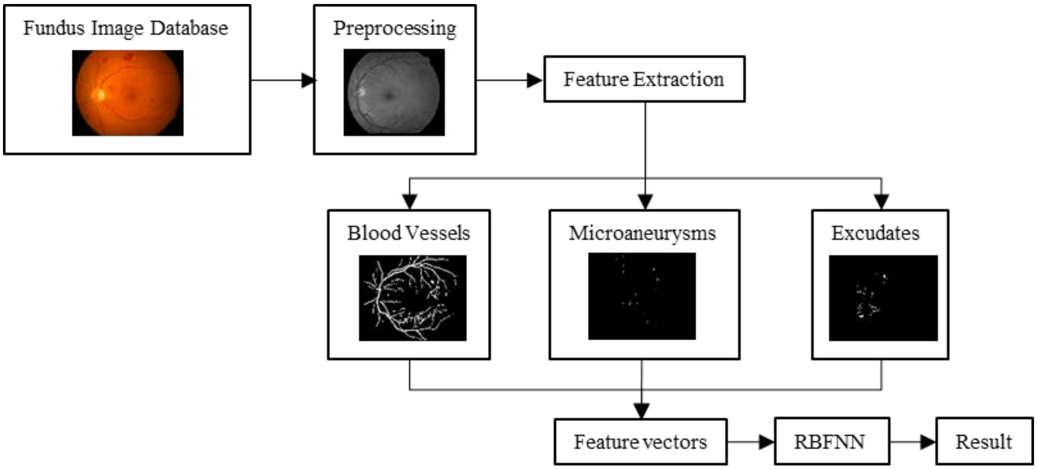


Fig. 1. Diabetic retinopathy system using RBFNN

Preprocessing: Initially captured database fundus retinal images are non-uniform illumination, with noise & poor contrast. The presence of these drawbacks are reduced by preprocessing and make suitable image to extract features. Preprocessing follows the steps as 1) RGB image converted to gray scale image. 2) Histogram equalization to contrast adjustment. 3) It is important to reduce effect of noise thus it is necessary to smoothing image by (wiener) filtering [10].

Optical disk seems like exudate by their characteristics like size, color tone in exposure result, so to minimize confusion in feature extraction process. Necessity to mask out the optical disk by using A-IFS histon based segmentation method & formulated as shown in equation 1[10][11].

$$F_i(g) = \sum_{m=1}^{M} \sum_{n=1}^{N} \big(1 + \mu(m,n)\big)\, \delta(I(m,n,i) - g) \tag{1}$$

For $0 \leq g \leq L - 1$ and $i = \{L, a, b\}$; Where $\mu(m,n)$= Gaussian membership function

Blood Vessel Extraction: 1) Digital Fundus image. 2) Perform HSV Transformation. 3) Image Standardization using Bi-cubic interpolation. 4) Perform Gamma correction on the standardized Image. 5) Background subtraction / segmentation by 2d Gabor filtering approach stated in equation 2 and 3[10]. 6) Threshold value Detection by Histogram analysis. 7) Perform simple binary thresholding to detect possible Blood vessels. 8) Perform opening operation to accurately detect Blood vessels, and 9) finally detected blood vessels.

$$\mathrm{G}(\mathrm{x},\mathrm{y}) = \exp\left\{-\left(\frac{\mathrm{x}_1^2}{\sigma_\mathrm{x}^2} + \frac{\mathrm{y}_1^2}{\sigma_\mathrm{y}^2}\right)\right\} \cos\left(\frac{2\pi \mathrm{x}_1}{\lambda}\right) \tag{2}$$

where $x_1 = y_1 = xcos\theta + ysin\theta$ and $\sigma_x = \sigma_y = \sigma$

$$G(x,y) = \exp\left(\frac{2x_1^2}{\sigma^2}\right) \cos\left(\frac{2\pi x_1}{\lambda}\right) \tag{3}$$

15×15 a window size provide a precise outcome. Miscellaneous width is σ for the small and the large Blood vessels [10] [11].

Exudates Extraction: 1) digital color fundus image. 2) Perform brightness correction using HSV color in image. 3) Image Standardization using Bi-cubic interpolation. 4) Perform Gamma correction on the standardized Image. 5) Threshold value Detection by Histogram analysis. 6) Perform simple binary thresholding to detect possible exudates. 7) False positive removal using multi-channel histogram analysis, and 8) finally detected white lesion [11].

Microaneurysms Extraction: 1) Digital retinal image. 2) Part 1 contain a) Image processing b) numerical morphology based retinal image extraction c) identification of retinal image by binary thresholding. 3) Part 2 contain a) Elimination of non-red lesions on the blood vessels b) elimination of non-red lesions in the optic disk area. 4) Lastly detected red lesion [11].

3.3. Radial Basis Function

One of the One of the particular type of ANN (artificial neural network) is RBF that uses as activation functions. RBF belongs to four layer feed forward network illustrated in fig 2 [5] [13] [14].

1'st layer i.e. input layer which includes D numeral of neurons, where D states as input design measurement. Input layer and pattern layer is completely linked with each other [5] [6].

2'nd layer i.e. Pattern layer which includes H numeral of neurons. H < N; where N stated as number of training forms. Pattern layer and summation layer is completely linked with each other no weights. Respective neuron of pattern layer is statistically termed as Gaussian RBF illustrated in below eq. 4-6 [5].

$$\varphi_{ij}(x) = \varphi(x - \mu_{ij});\ i = 1,2, \ldots..,P, j = 1,2, \ldots, Q_i \tag{4}$$

$$\varphi_{ij}(x) = \frac{1}{\sqrt{2\pi}\sigma_{ij}} e^{-\frac{(x-\mu_{ij})^2}{2(\sigma_{ij})^2}} \tag{5}$$

$$H = \sum_{i=1}^{P} Q_i \tag{6}$$

where

- I =Separate class no in data
- P =max. no of classes
- J =cluster no inside the class
- Q_i =maximum of clusters inside i^{th} class
- x =pattern presented at i/p layer
- μ_{ij} =mean vector of j^{th} cluster in i^{th} class
- σ_{ij} =cluster variance of j^{th} cluster in i^{th} class

Pattern layer belongs to Gaussian activation functions. The Gaussian functions categorized into mean vectors (centers) μ_{ij} and shapes (spreads) σ_{ij} of the groups (clusters).

3'rd layer i.e. Summation layer is having small number of neurons and linear activation functions. Summation layer is having limited size to number of distinct classes to training data. O/p of the k^{th} neuron in this layer illustrated by Eq.7 [5].

$$S_k(x) = \sum_{i=1}^{P} \sum_{j=1}^{Q_i} W_{ij}^{k} \phi_{ij} \quad , \qquad k = 1,2, \ldots, P \tag{7}$$

where

- I =W_{ij}^{k} = weight between ϕ_{ij} pattern neuron
- k^{th} = summation layer neuron

- S_k = output of k^{th} neuron in summation layer

4'th layer i.e. Decision layer consist of single neuron. It o/p the class label of testing pattern. The o/p of i^{th} class for test pattern x given in equation 8 [5].

$$Class(x) = \max_{i} S_i\,(x), \qquad i = 1,2, \dots, P \tag{8}$$

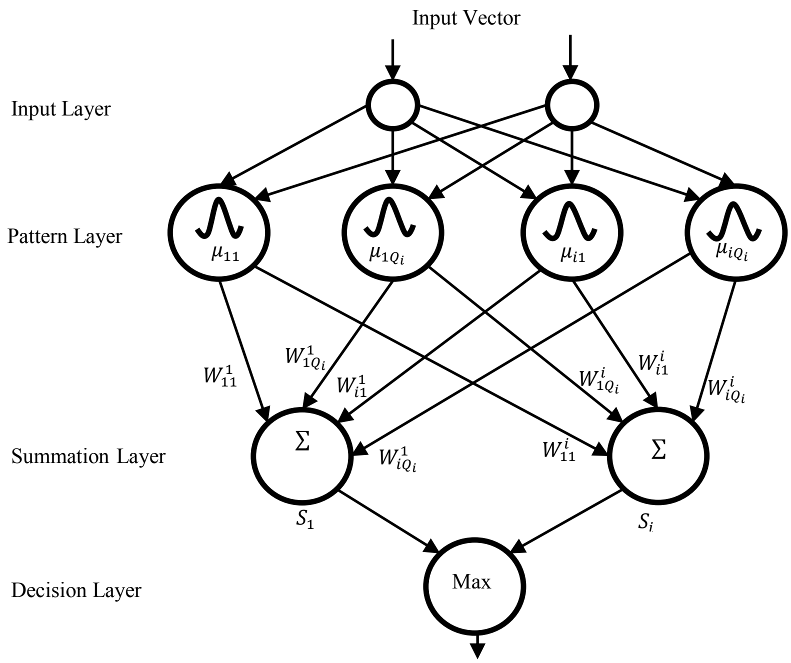


Fig. 2. RBF Neural Network

4. Experimental Result

Matlab Platform is utilized to perform experimental implementation and its evaluation. A GUI (graphical user interface) is developed for proposed system and it is shown in fig 3. In GUI there is browser button to take test image. From this test image, features namely exudate, Blood vessels and microaneurysms were extracted and classify the image as Non DR or DR by using RBF Classifier.

Statistical assessment has been done by using Formulae of Mean, Variance (Var), SD (Standard Deviation) and Correlation shown in eq. 9-12 respectively [12] and these formulae calculate the statistical values of Exudates, Blood Vessels & Microaneurysms for each test sample.

$$\text{Mean} = \frac{\text{sum of component}}{\text{no of component}} \tag{9}$$

$$\text{Var} = \frac{\sum(\text{x} - \bar{\text{x}})}{\text{N}} \tag{10}$$

$$\text{SD} = \sqrt{\text{Var(x)}} \tag{11}$$

$$\text{Correlation (r)} = \frac{\sum(x - \bar{X})\sum(y - \bar{Y})}{\sqrt{\sum(x - \bar{X})^2 \sum(y - \bar{Y})^2}} \tag{12}$$

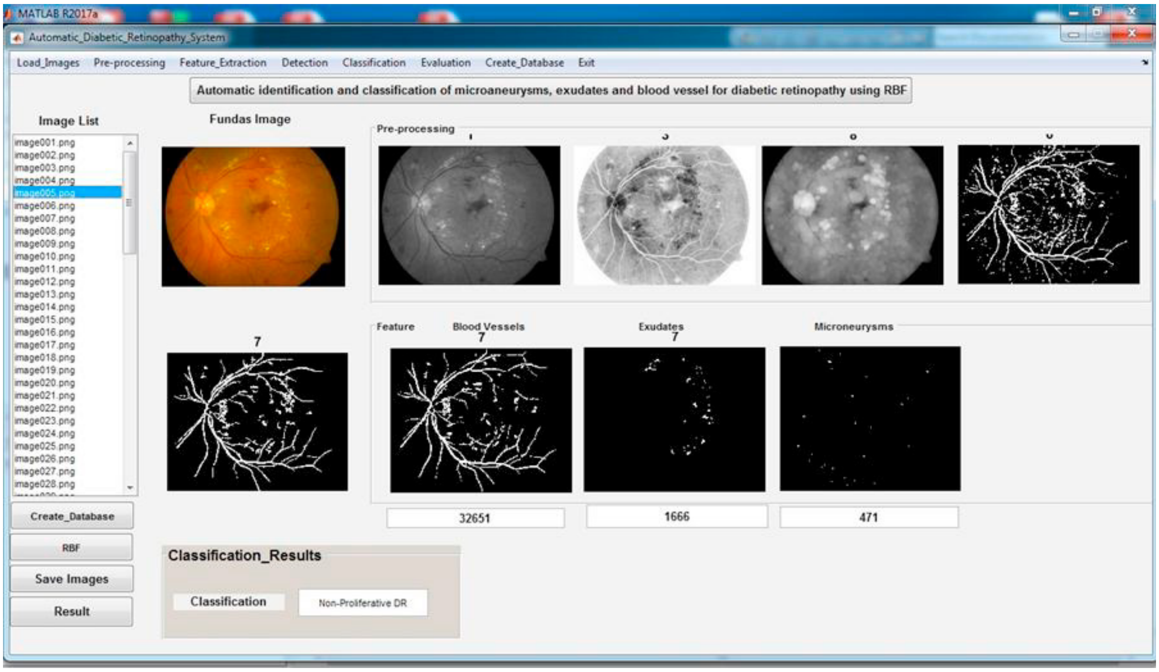


Fig. 3. Design of GUI for proposed system.

Arithmetical constraint of Blood Vessels, Exudates & Microaneurysms shown in the table 2-4 respectively for 5 image samples. In this manner image dataset can be calculated.

Table 2. The arithmetic constraint of Blood Vessels

Sr. No.	Image	Diameter (x)	Tortuosity (y)	$(x - \bar{X})$	$(y - \bar{Y})$	$(x - \bar{X}) * (y - \bar{Y})$	(xy)
1	10_Image	12	12	11.53	11.86	136.77	144
2	11_Image	16	8	15.53	7.86	122.07	128
3	12_Image	12	2	11.53	1.86	21.43	24
4	13_Image	12	14	11.53	13.86	159.84	168
5	14_Image	16	1	15.53	0.86	13.33	16

Table 3. The arithmetic constraint of Exudates.

Sr. No.	Image	Manual Counting Of Exudates (x)	Exudates by Algorithm (y)	$(x - \bar{X})$	$(y - \bar{Y})$	$(x - \bar{X}) * (y - \bar{Y})$	(xy)
1	10_Image	31	31	29.24	29.19	853.55	961
2	11_Image	68	68	66.24	66.19	4384.5	4624
3	12_Image	18	18	16.24	16.19	262.94	324

4	13_Image	41	41	39.24	39.19	1537.86	1681
5	14_Image	96	96	94.24	94.19	8876.57	9216

Table 4. The arithmetic constraint of Microaneurysms

Sr. No.	Image	Manual Counting of Microaneurysm (x)	Microaneurysm by Algorithm (y)	$(x - \bar{X})$	$(y - \bar{Y})$	$(x - \bar{X}) * (y - \bar{Y})$	(xy)
1	10_Image	932	932	915.61	915.24	838002.9	868624
2	11_Image	889	905	872.61	888.24	775087.11	804545
3	12_Image	204	204	187.61	187.24	35128.1	41616
4	13_Image	795	795	778.61	778.24	605945.45	632025
5	14_Image	891	891	874.61	874.24	764619.05	793881

The performance evaluation of the projected system in this paper has been studied in terms of sensitivity, specificity and accuracy. Sensitivity means disease diagnosis is correct (Diabetic retinopathy recognition is positive i.e. DR characteristics present in retinal images). Specificity means disease diagnosis is incorrect (Diabetic retinopathy recognition is negative i.e. Non DR characteristics present in retinal images) [12]. Outcome of proposed system shown in table 5.

Table 5. Performance Evaluation for DIARETDB1 and DIARETDB0 database.

Test	Positive		Negative		Sensitivity	Specificity	Accuracy
	True positive (TP= no of retinal images correctly identified)	False positive (FP= no of retinal images incorrectly identified)	True negative (TN= no of retinal images correctly rejected)	False negative (FN= no of retinal images incorrectly rejected)	Sensitivity = $\frac{TP}{(TP+FN)}$	Specificity = $\frac{TN}{(TN+FP)}$	Accuracy = $\frac{TP+TN}{(TP+TN+FP+FN)}$
Db1 (89)	84	5	1	5	0.943(94.3%)	0.16(16.0%)	0.894(89.4%)
Db0 (130)	108	22	1	22	0.830(83.0%)	0.043(0.04%)	0.712(71.2%)

The proposed system achieved the 0.943 Sensitivity, 0.16 Specificity and 0.894 accuracy for DIARETDB1 and 0.830 Sensitivity, 0.043 Specificity & 0.712 accuracy for DIARETDB0 shown in table 2.

The receiver operating characteristic (ROC) curve has been determined for DIARETDB1 and DIARETDB0 database illustrate in fig 4 (a) & (b) individually.

Consequent parameters (Sensitivity, Specificity, accuracy) of proposed system are compared with the previously published papers as shown in table 6.

Table 6. Comparison result of the proposed system with previously published papers

Author	Database	Extracted Ophthalmic features	Classifier	Result
Maria Garcia et al. [3]	IOBA of the spain	Exudate	RBF	Sensitivity-92.1% Specificity-70.4%
M. Garcia et al. [4]	IOBA of the spain	Hemorrhages and microaneurysms	RBF	Sensitivity-86.0% Specificity -56.0%

Mohamed Chetoui et al. [17]	MESSIDOR	Exudates, hemorrhages and microaneurysms	SVMRBF	Accuracy-0.904 (LESH) Accuracy- 0.841 (LTP)
Proposed system	DIARETDB1(Db1)	Exudates, blood vessels & micro aneurysms	RBF	Sensitivity-94.3% (Db1) Specificity-16.0% (Db1) Accuracy-89.4% (Db1)
	DIARETDB0(Db0)			Sensitivity-83.0% (Db0) Specificity-0.04% (Db0) Accuracy-71.2% (Db0)

a b

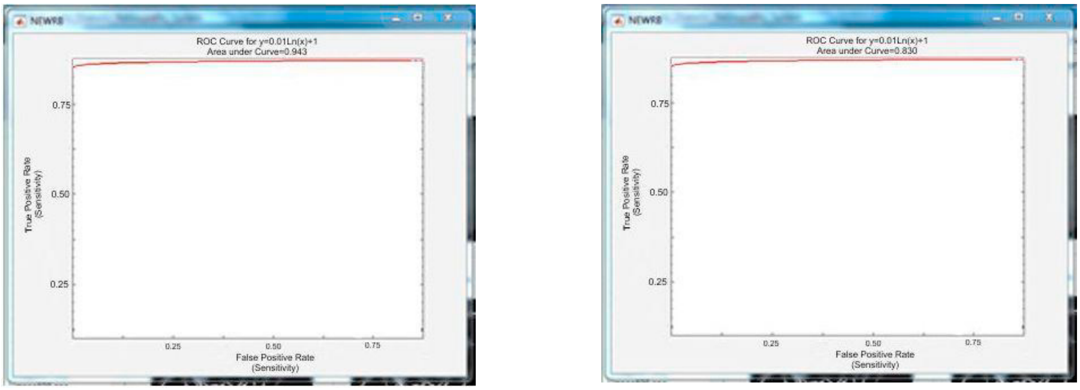


Fig. 4. (a) ROC of DIARETDB1; (b) ROC of DIARETDB0.

5. Conclusion

The intended system is established to detect retinal images as DR (diabetic retinopathy) or No DR by using RBF classifier. Initially preprocessing, segmentation has been done for fundus images and then extracted features namely exudates, blood vessels and micro aneurysms from images. By using these features RBF NN gets trained. DIARETDB0 and DIARETDB1 dataset was employed execute experiment. From the experimental analysis it is observed that the intended system yielded 0.83 Sensitivity & 0.043 Specificity for DIARETDB0, whereas for 0.94 Sensitivity and 0.16 Specificity for DIARETDB1 has been observed. In future the proposed system can be incorporated with multiple classifier system (MCS) to pre detection of diabetic retinopathy. It can be useful to improve the performance of classifiers and also improve the accuracy of the system.

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