DETECTION OF DIABETIC RETINOPATHY USING RADIAL BASIS FUNCTION

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Abstract — Retinal exudates classification and identification of diabetic retinopathy to diagnose the eyes using fundus images requires automation. This research work proposes retinal exudates classification.

Approach: Representative features are obtained from the fundus images using contextual clustering (CC) segmentation methods. The number of features obtained is two. The radial basis function (RBF) network is trained by the features. Final weights are obtained and subsequently used for testing.

Results: The presence of exudates is identified more clearly as the CC uses neighbourhood information. By knowing the outputs of RBF during testing, accurate diagnosis and prescription for treatment of the affected eyes can be done. One hundred fundus images are used for testing. The performance of RBF is 96%(48 images are classified).

Conclusion: Simulation results show the effectiveness of RBF in retinopathy classification. Very large database can be created from the fundus images collected from the diabetic retinopathy patients that can be used for future work

Keywords: Diabetic retinopathy, fundus image, exudates detection, radial basis function, contextual clustering

I. INTRODUCTION

Diabetic Retinopathy (DR) cause blindness [1]. The prevalence of retinopathy varies with the age of onset of diabetes and the duration of the disease . Color fundus images are used by ophthalmologists to study eye diseases like diabetic retinopathy [2]. Big blood clots called hemorrhages are found. Hard exudates are yellow lipid deposits which appear 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 microaneurysms and hemorrhages[3], especially in relation to the fovea can be used to determine the severity of diabetic retinopathy

Hard exudates are shinny and yellowish intraretinal protein deposits, irregular shaped, and found in the posterior pole of the fundus [4]. Hard exudates may be observed in several retinal vascular pathologies. Diabetic macular edema is the main cause of visual impairment in diabetic patients. Exudates are well contrasted with respect to the background that surrounds them and their shape and size vary considerably [5]. Hard and soft exudates can be distinguished because of their color and the sharpness of their borders. Various methods have been reported for the detection of Exudates. Efficient algorithms for the detection of the optic disc and retinal exudates have been presented in [6][7].

Thresholding and region growing methods were used to detect exudates [8][9], use a median filter to remove noise, segment bright lesions and dark lesions by thresholding, perform region growing, then identify exudates regions with Bayesian, Mahalanobis, and nearest neighbor (NN) classifiers. Recursive region growing segmentation (RRGS).[10], have been used for an automated detection of diabetic retinopathy Adaptive intensity thresholding and combination of RRGS were used to detect exudates,[11], [12], combine color and sharp edge features to detect exudate. First they find yellowish objects, and then they find sharp edges using various rotated versions of Kirsch masks on the green component of the original image. Yellowish objects with sharp edges are classified as exudates.

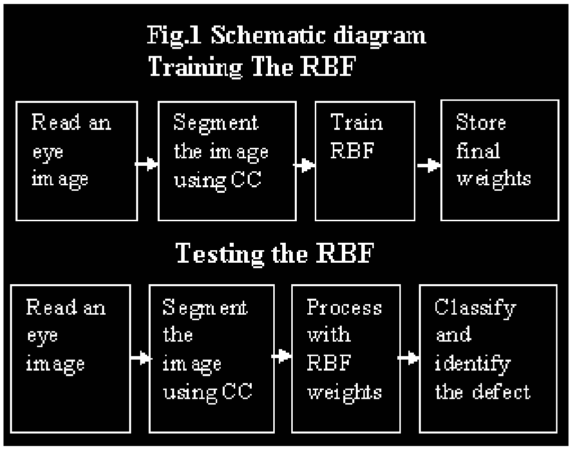


Fig.1 Schematic diagram

II. MATERIALS AND METHODS

This research work proposes contextual clustering (CC) and Radial Basis Function (RBF) network. CC is used for feature extraction. The extracted features are input to the RBF network. In order to achieve maximum percentage of identification of the exudates, proper data input for RBF, optimum topology of RBF and correct training of RBF with suitable parameters is a must.

A large amount of exudates and non exudates images are collected. Features are extracted from the images using contextual clustering segmentation. The features are input to the RBF and labeling is given in the output layer of RBF. The labeling indicates the exudates. The final weights obtained after training the RBF is used to identify the exudates. Figure 1 explains the overall sequence of proposed methodology.

III.CONTEXTUAL CLUSTERING

Image segmentation is a subjective and context-dependent cognitive process. It implicitly includes not only the detection and localization but also the delineation of the activated region. In medical imaging field, the precise and computerized delineation of anatomic structures from image data sequences is still an open problem. Countless methods have been developed, but as a rule, user interaction cannot be negated or the method is said to be robust only for unique kinds of images.

Contextual segmentation refers to the process of partitioning a data into multiple regions. The goal of segmentation is to simplify and / or change the representation of data into something that is more meaningful and easier to analyze. Data segmentation is typically used to locate data in a vector. The result of contextual data segmentation is a set of regions that collectively cover the entire data. Each value in a data is similar with respect to some characteristics. Adjacent regions are significantly different with respect to the same characteristics. Several general-purpose algorithms and techniques have been developed for data segmentation. Contextual clustering algorithms segments a data into one category (ω_0) and another category (ω_1). The data of the background are assumed to be drawn from standard normal distribution.

1. Define decision parameter T_{cc} (positive) and weight of neighbourhood information β (positive). Let N_n be the total number of data in the neighbourhood. Let Z_i be the data.
2. Initialization: classify element of data with $Z_i > T_{cc}$ to ω_1 and element of data to ω_0. Store the classification to C_0 and C_1.
3. For each element of data 'i', count the number of data u_i, belonging to class ω_1 in the neighbourhood of data 'i'. Assume that the element of data outside the data area belong to ω_0.
4. Classify element of data with $z_i + \frac{\beta}{T_{cc}}(u_i - \frac{N_n}{2}) > T_\alpha$ to ω_1 and other element of data to ω_0. Store the classification to variable C_2.
5. If $C_2 \neq C_1$ and $C_2 \neq C_0$, copy C_1 to C_0, C_2 to C_1 and return to step 3, otherwise stop and return to C_2.[13]

IV.RADIAL BASIS FUNCTION

Radial basis function neural network (RBF) is a supervised neural network. The network has an input layer, hidden layer (RBF layer) and output layer. The 2 features obtained are used as inputs for the network and the target values for training each exudate is given in the output layer.

Training RBF is done as follows:

1. Finding distance between pattern and centers .
2. Creating an RBF matrix whose size will be (np X cp).(Figure 2) , where np = number of pattern used for training and cp is number of centers which is equal to 10. The number of centers chosen should make the RBF network learn the maximum number oftraining patterns under consideration.

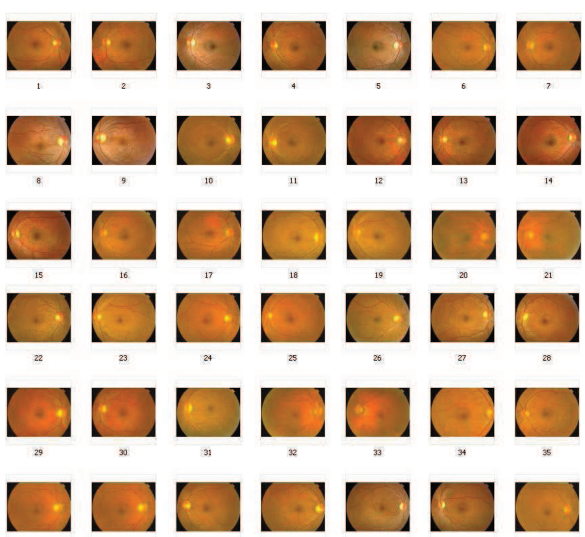
3. Calculate final weights which is inverse of RBF matrix[14][15][16][17][18] multiplied with Target values.
4. During testing, the performance of the RBF network, RBF values are formed from the features obtained from CC and processed with the final weights obtained during training. Based on the result obtained, the image is classified to have a type of exudate or not.

V. EXPERIMENTAL WORK

Color retinal images obtained from Aravind Hospitals, Madurai (India). According to the National Screening Committee standards, all the images are obtained using a Canon CR6-45 Non-Mydriatic (CR6-45NM) retinal camera. A modified digital back unit (Sony PowerHAD 3CCD color video camera and Canon CR-TA) is connected to the fundus camera to convert the fundus image into a digital image. The digital images are processed with an image grabber and saved on the hard drive of a Windows 2000 based Pentium -IV.

The Sample images of normal (Figure 2) and abnormal types (Figure 3)are given.

Fig. 2 Normal fundus images



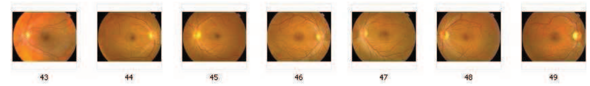


Fig.3 Hardexudates

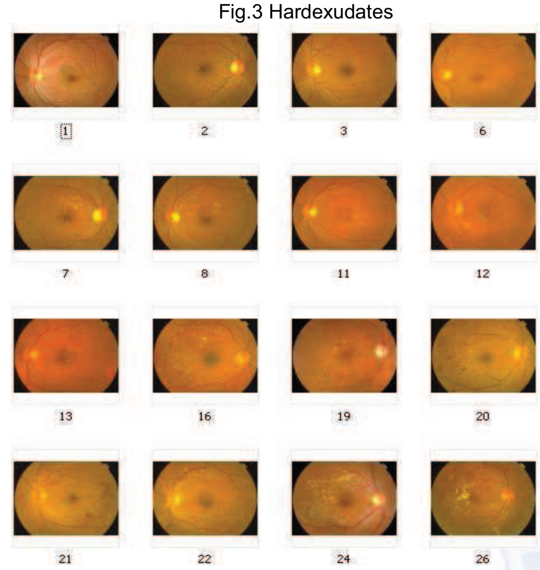


Figure 2 shows sample images of eyes in good condition. Figure 3 shows sample images of eyes with hard exudates.

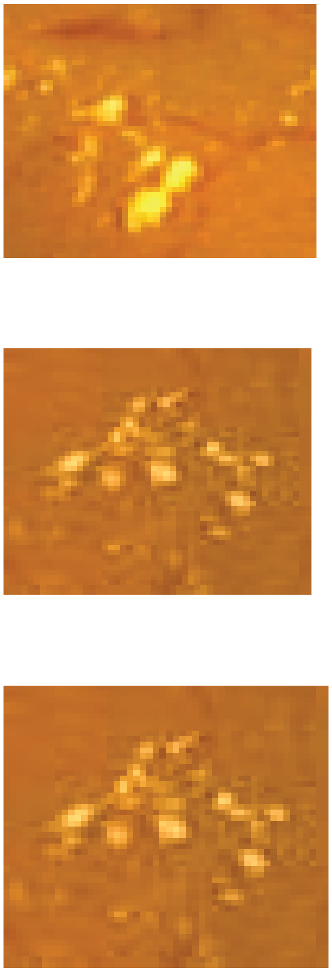
VI. RESULTS AND DISCUSSION

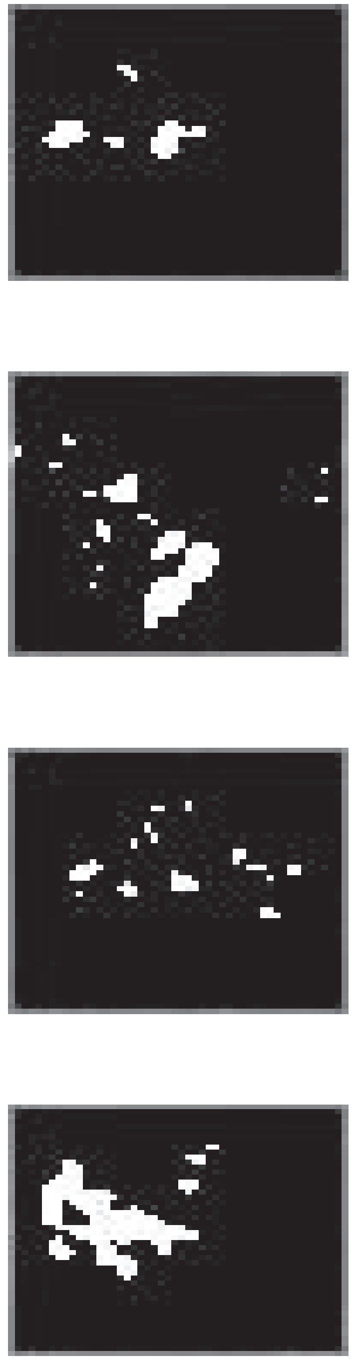
For template matching and comparison purposes, representative exudates are isolated from the original retinopathy images in order to create exudates templates which are presented in

Figure 4.

Fig. 4: Segmented pictures of hard exudates

(a)Sample Hard Exudates





(b) Segmented hard exudates by CC

Figure 4a shows the sample templates out of one hundred templates collected. Each template has varied scattering of the exudates. Figure 4b shows , the segmented exudates by the CC method. The black indicates the background of the image and the white shows the hard exudates. CC does effective segmentation. Statistical features for the hard exudates templates are found. The statistical features considered are 'Convex Area', 'Solidity',' Orientation' and 'Filled Area'. In Fig. 5a, different stages of outputs of CC are given. The entire image processing included here involves normalizing, histogram equalization, segmentation.

Fig.5a A portion of the original true color image

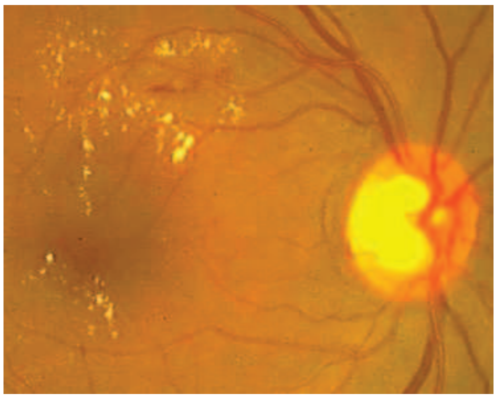


Figure 5a presents a portion of the original diabetic retinopathy image in true color. The plane-1 information of the original image is shown in Figure 5b. The plane-2 (Figure 5c) and plane-3(Figure 5d) are shown. Identification of exudates is done using plane-2 information.

Fig.5b Plane 1 of the image in Figure 5a

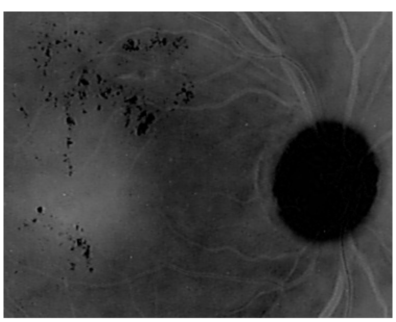


Fig.5c Plane 2 of the image in Figure 5a

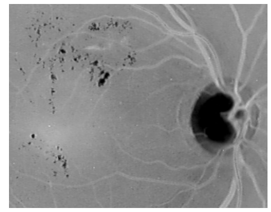


Fig.5d Plane 3 of the image in Figure 5a

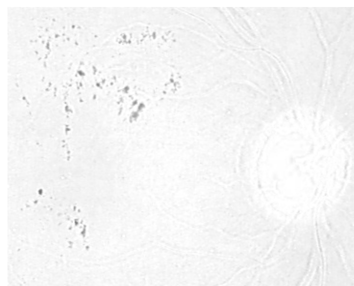
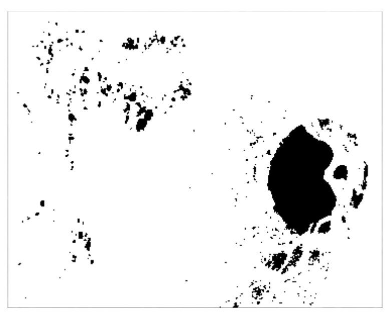


Fig.5e Plane 2 of the image segmented by using CC



The hard exudates are found scattered in the retinopathy image. The segmented image of CC shows more noise. Noise is present in CC segmented image. Figure 6a presents 9 pixel values summed versus the window number during scanning the image to be segmented. The average summed number is above 1500 which is an indication of slight white background appearance as can be seen from Figure 5c (plane 2).

Fig.6a Total pixel values

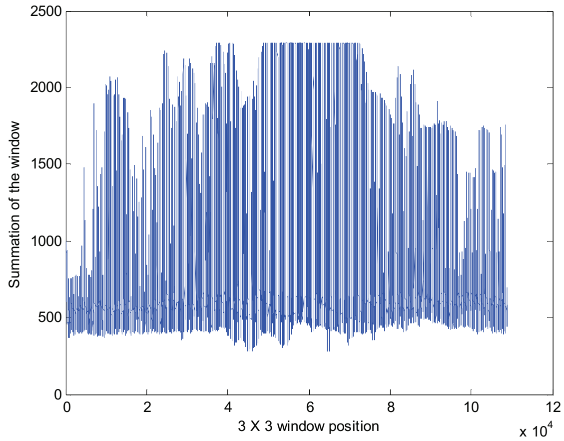
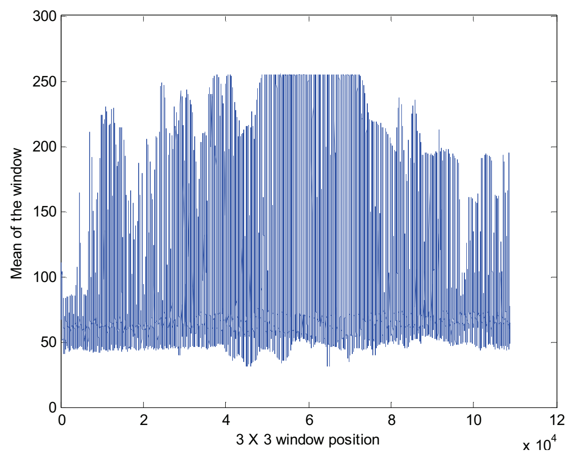
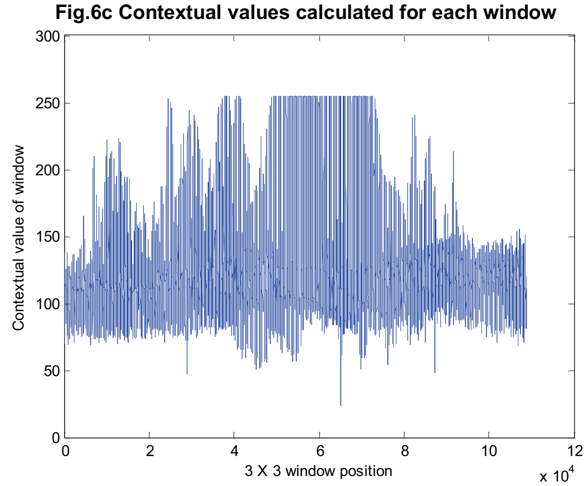


Fig.6b Mean of each window



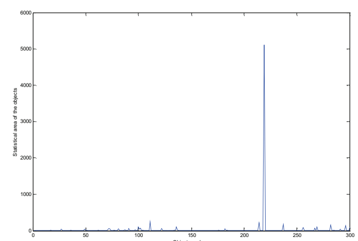
The mean (Figure 6b) and the contextual values (Figure 6c) are shown.

Fig.6c Contextual values calculated for each window



The property of imfeature is applied to the segmented image. The area of the labeled objects in the segmented image are obtained. The optic disc in the image is removed by using a threshold. If the area of an object is greater than a value of 500, then it is treated as optic disc. Using the boundingbox concept, this object is filled with black. Hence the remaining objects could be either the noise or the exudates. Figure 7 shows the edydisc removed by applying statistical features.

Fig.7 Eyedisc removed



The sample outputs of statistical area of the imfeature is shown in Table 1.

Implementation of RBF

Table 1 Data for training RBF

Training Inputs				Target outputs
Area	Filled Area	Solidity	Orientation	Labeling
55	59	0.6111	-16.5837	1
59	59	0.7024	-29.5294	1
61	61	0.5980	43.1644	1
64	64	0.5161	-4.1202	1
69	70	0.6970	20.1090	1
75	75	0.7732	7.9202	1
78	80	0.6393	82.4571	1
89	91	0.5973	84.0033	1
100	101	0.5587	-39.8444	1
104	108	0.7324	-12.7048	2
109	109	0.8790	42.4872	2
139	139	0.7128	81.1306	2
165	165	0.9016	45.6726	2
167	180	0.5860	55.3490	2
214	219	0.7431	40.4485	2
251	251	0.6452	80.2676	2
5108	5117	0.8913	91.3917	2

The RBF is trained with the data given in Table 1. Each row made up of 4 variables. A labeling is given in the last column. Eighteen patterns are considered for training RBF. These 18 patterns are taken from the segmented image given in Figure 5e. Additional hard exudate images can also be considered from which additional patterns can be obtained. A topology of $4_{(\text{nodes in the input layer})}$ X $5_{(\text{nodes in the hidden layer})}$ X $1_{(\text{node in the output layer})}$ is used for training RBF. The final weights obtained is used for classification of the segmented exudates from the noise present in the segmented image.

VII. CONCLUSION

The main focus of this work is on segmenting the diabetic retinopathy image and classify the exudates. Segmentation is done using contextual clustering and classification of the exudates is done using radial basis function (RBF) network. The performance classification of exudates by using RBF and CC is better than that of using only CC. The proposed RBF classifies the segmented information of the image into hard exudates or not.

1. All the fundus images in this work have to be transformed to a standard template image condition. This corrects in the illumination effect on the images.
2. Only when the fundus image is taken with good quality, detection of exudates is more accurate.

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