DOI: 10.21917/ijivp.2012.0071

AN IMPROVED MEDICAL DECISION SUPPORT SYSTEM TO GRADING THE DIABETIC RETINOPATHY USING FUNDUS IMAGES

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Abstract

An improved Computer Aided Clinical Decision Support System has been developed for grading the retinal images using neural network and presented in this paper. Hard exudates, Cotton wool spots, large plaque hard exudates, Microaneurysms and Hemorrhages have been extracted. SVM classifiers have been used for classification. Further rule based classifiers have been used to grade the retinal images. The percentages of sensitivity, specificity have been found for both bright lesions and dark lesions. The accuracy of the proposed method is capable of detecting the bright and dark lesions sharply with an average accuracy of 98.19% and 97.51% respectively.

Keywords:

Bright Lesion, Dark Lesion, Hard Exudates, Cotton Wool Spots, LPHE, Microaneurysms, Hemorrhages, SVM, Diabetic Retinopathy (DR), Non Proliferative Diabetic Retinopathy (NPDR)

1. INTRODUCTION

Diabetic retinopathy (DR) is found to be a leading cause of blindness due to the leakage of blood vessels of retina. These weakened blood vessels will leak blood to spread over the retina, which in turn forms microaneurysms, hemorrhages, hard exudates, cotton wool spots and Large Plaque Hard Exudates (LPHE). DR is a progressive disease which can advance from mild stage to proliferative stage. It was found that four stages such as Mild non proliferative diabetic retinopathy, Moderate non proliferative diabetic retinopathy, severe non proliferative diabetic retinopathy and Proliferative diabetic retinopathy can exist. Mild non Proliferative diabetic retinopathy results due to the presence of at least one micro aneurysm. Micro aneurysms are small, round and dark red dots with sharp margins and are the first detectable signs of retinopathy. Moderate non Proliferative retinopathy results due to the presence of numerous microaneurysms, cotton wool spots and hard exudates. Hemorrhages are bigger than microaneurysms and occur at the various levels of retina especially at the venous end of the capillaries. Hard exudates are shiny, irregular shaped and are found near prominent micro aneurysms, cotton wool spots or soft exudates are infractions in the nerve fiber layers of retina which are round or oval shape, pale yellow or white in color. Severe non Proliferative diabetic retinopathy is characterized by any one of the following (4:2:1) rule characteristics a) Numerous hemorrhages and micro aneurysms in four quadrants of the retina, b) Venous beading in two or more quadrants, c) Intra retinal Micro vascular Abnormalities in at least one or more quadrant (IRMA) and d) Severe non Proliferative diabetic retinopathy is characterized by any two of the signs of severe non proliferative diabetic retinopathy.

Proliferative retinopathy is the advanced stage of the DR and the signs are characterized by any one or more of the following; a) Pre retinal hemorrhages, b) Vitreous hemorrhages, c) Neovascularization which is growth of abnormal new vessels on the inner surface of the retina that are divided into two categories namely New Vessels over Disc (NVD) and New Vessels Elsewhere except disc (NVE). These analysis has been presented by many researchers in the past and continue to do the same.

Ahmed Wasif Reza and Easwaran[1] have developed the method to detect an automatic screening system for detecting the early stages of bright lesions of DR .This involves processing of fundus images for the extraction of abnormal signs, such as hard exudates, cotton wool spots, and large plaque of hard exudates. A rule based classifier is used for classifying the DR into two classes, namely, normal and abnormal. The abnormal NPDR is further classified into three levels, namely, mild, moderate and severe. Ahmed Wasif Reza *et.al*., [2] have developed a system Automatic Extraction of Optic Disc and Exudates from retinal Images using Marker-controlled Watershed Transformation Optic disc (OD), exudates, and cotton wool spots are the main features of fundus images which are used for diagnosing eye diseases, such as diabetic retinopathy and glaucoma. Ahmed Wasif Reza *et.al*.,[3] have developed Automatic tracing of optic disc and exudates from color fundus images using fixed and variable thresholds that automatically segment the OD and exudates.

Ahmed Wasif Reza *et.al*., [4] have developed A Quad tree Based Blood Vessel Detection Algorithm using RGB Components in fundus images that proposes a novel computational paradigm for detection of blood vessels in fundus images based on RGB components and quad tree decomposition. The proposed algorithm employs median filtering, quad tree decomposition, post filtration of detected edges and morphological reconstruction on retinal images. C. Eswaran *et.al*., [5] have developed extraction of the contours of optic disc and exudates based on Marker Controlled Watershed segmentation algorithm that was capable of tracing the boundaries of the optic disc and exudates sharply yielding the exact contours.

S Kavitha and Duraiswamy [6] have developed a methodology to automatically detect the hard and soft exudates in fundus images using color histogram thresholding. A series of experiments on classification of hard and soft exudates was performed with the use of image processing techniques. Subsequently nonlinear diffusion segmentation was employed to encapsulate the variation in exudates and lesion boundary criteria pixels. To prevent the optic disc from interfering with exudates detection, the optic disc is detected and localized with

the aid of region props and color histogram. Asha Gowda *et.al*., [7] have reported exudates detection in retinal Images using back propagation neural network. To prevent the optic disc from interfering with exudates detection, the optic disc is eliminated. Significant features are identified from the images after preprocessing by using two methods: Decision tree and GA-CFS method are used as input to the BPN model to detect the exudates and non-exudates at pixel level.

U R Acharya *et.al*., [8] have developed an automated Computer-based detection of diabetes retinopathy stages using digital fundus images. Morphological image processing and support vector machine (SVM) techniques were used for the automatic diagnosis of eye health. Five groups were identified: normal retina, mild non-proliferative diabetic retinopathy, moderate non-proliferative diabetic retinopathy, severe non-proliferative diabetic retinopathy, and proliferative diabetic retinopathy. Four salient features blood vessels, micro aneurysms, exudates, and hemorrhages were extracted from the raw images using image-processing techniques and fed to the SVM for classification. L. Giancardo *et.al*., [9] have developed Automatic retina exudates segmentation without a manually labeled training set. Two new methods for the detection of exudates are presented. Vijayamadheswaran and Arthanari [10] have developed detection of diabetic retinopathy using radial basis function. The presence of exudates is identified more clearly as the contextual clustering uses neighborhood information. By knowing the outputs of RBF during testing, accurate diagnosis and prescription for treatment of the affected eyes can be done. Maria Garcia and Maria[11] have developed an assessment of four neural network based classifications to automatically detect red lesions in retinal images. The aim is to automatically detect one of such early signs, red lesions, like hemorrhages and micro aneurysms. Neural network based classifiers were subsequently used to obtain the final segmentation of red lesions.

Deepak Villach *et.al*., [12] have developed a method for automated detection and classification of vascular abnormalities in diabetic retinopathy. The vascular abnormalities are detected using scale and orientation selective Gabor filter banks. The proposed method classifies the retinal image as mild or severe case based on the outputs obtained from Gabor filters. Maria Garcia *et.al*., [13] have reported detection of hard exudates in retinal images using a radial basis function classifier. The aim of this study was to automatically detect these lesions in fundus images. To achieve this goal, each image was normalized and the candidate regions were segmented by a combination of global and adaptive thresholding. Then a group of features was extracted from image regions and the subset which best discriminated between exudates and retinal background was selected by means of logistic regression.

Meindert Niemeyer *et.al*., [14] have developed Retinopathy online challenge automatic detection of micro aneurysms in digital color fundus Photographs. A human expert detected micro aneurysm in the test set to allow comparison with the performance of the automatic methods. The overall results show that micro aneurysm detection is a challenging task for both the automatic methods as well as the human expert.

Meindert Niemeijer *et.al*., [15] have developed an automated detection and differentiation of drusen, exudates and cotton wool spots in digital color fundus Photographs for diabetic retinopathy diagnosis was developed. This method describes and evaluates a machine learning based, automated system to detect exudates and cotton wool spots in digital color fundus photographs and differentiate them from drusen, for early diagnosis of diabetic retinopathy methods. Gwenole Quellec *et.al*., [16] have developed Optimal wavelet transform for the detection of micro aneurysms in retina photographs propose an automatic method to detect micro aneurysms in retina photographs. Micro aneurysms are the most frequent and usually the first lesions to appear as a consequence of diabetic retinopathy. Images are of three different modalities: there are color photographs, green filtered photographs, and angiographs. Depending on the imaging modality, micro aneurysms were detected.

This paper presents the automated detection and grading of the retinal images based on the presence of hard exudates, cotton wool spots, LPHE, micro aneurysms and hemorrhages. Human experts standard for 90 images was obtained by consensus annotation by three retinal specialists. The proposed method consists of the following steps.

2. IMPLEMENTATION OF PROPOSED SYSTEM

The flow diagram of the proposed medical decision support system for classifying and grading the retinal image is shown in Fig.1. The proposed method consists of Image preprocessing, Segmentation, Feature extraction, Classification and Decision making.

2.1 DATA ACQUISITION AND PREPROCESSING

The retinal images of Normal, Mild non proliferative diabetic retinopathy, Moderate non proliferative diabetic retinopathy, severe non proliferative diabetic retinopathy and Proliferative diabetic retinopathy have been obtained from Bejan Singh Eye Hospital, Nagercoil, India. The images are acquired with dedicated fundus camera and digitized with a laser film scanner (ZE ISS Stratus OCT, Model 3000).

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, cotton wool spots, hemorrhages and microaneurosyms. Hence an image denoising and enhancement is required to preserve the image, highlighting the image feature and suppressing the noise. In the present work, Green channel separation and Image normalization techniques has been used for preprocessing.

2.1.1 Green Channel Extraction:

RGB to Gray conversion can be used to extract the Green channel from the input image and then enhanced using contrast enhancement. The differences in luminosity, contrast and brightness inside make it complex to extract retinal features and make distinction of hard exudates and cotton wool spots, from other bright features in images. Hence green channel extraction is required to preserve the image [1, 8].

2.2 OPTIC DISC IDENTIFICATION/ELIMINATION

The optic disc has the characteristics like, bright intensity, hard exudates and cotton wool spots. Identification of an optic

disc is a vital step in the automated retinal image screening system [3]. The optic disc is exemplified by the largest high contrast among circular shape areas. Since it is noticed to be in oval shape the optic disc is detected and removed to reduce false positives. First the area of interest namely the optic disc is selected using region of interest from the preprocessed image. This is achieved by searching the brightest area with an approximate diameter of an average optic disc.

Elimination of the optic disc is achieved by using masking operation. Once the optic disc is located then a mask is created [6, 7]. The size of the mask depends on the diameter of an optic disc. Then the created mask is applied to the identified optic disc in a retinal image. By using this procedure an optic disc is eliminated from the retinal image. This easily identifies the hard exudates, cotton wool spots and LPHE.

2.2.1 Block Processing:

The whole image is sub divided into 10 × 10 matrix sub images. This is mainly used for adjusting the luminance level of the images and to get the exact features of the bright lesions. The intensity of the image is not even throughout the images. The exudate in a darker area is darker compared to the exudates in a brighter area. To avoid this block processing method is used.

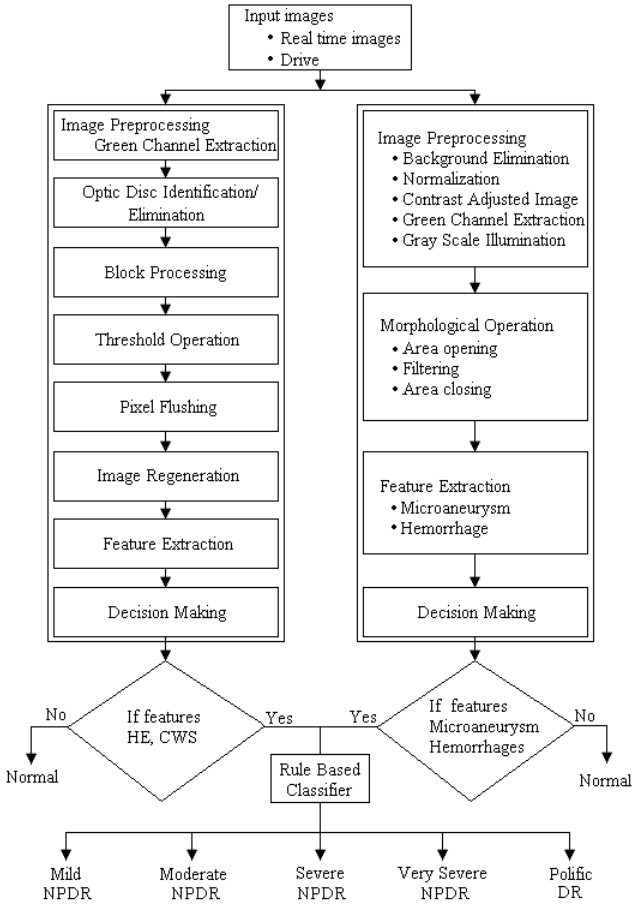


Fig.1. Flow diagram for proposed decision support system for classifying and grading of retinal images

2.2.2 Thresholding Operation:

To isolate the bright lesions from the back ground of the gray image a threshold value T is chosen [1, 3].The variable threshold is used for the feature of the bright lesions of the retinal images. This thresholding operation has been done for two groups of pixels, $G_1(x, y)$ and $G_2(x, y)$ as illustrated in Eq.(1) operation variable because of the luminous intensity.

$$G(x,y)=\begin{Bmatrix} 1(white)\,if\ G_1(x,y)\geq T \\ 0(black)\,if\ G_2(x,y)<T \end{Bmatrix} \quad (1)$$

The output binary image $G(x, y)$ is obtained in Eq.(1) the threshold value T turns every pixel value as black or white according to whether its value is greater than or less than T. In particular the output binary image has values of 1 (white) for all pixels in the image with luminance greater than level and 0 (black) for all other pixels.

2.2.3 Pixel Flushing:

In variable threshold operation, for each block, the maximum, minimum and mean pixel values of each block have been calculated. Based on these three values the variable threshold value has been selected. If the mean value is nearer to minimum pixel value then the whole block is removed by replacing all the pixels by 0. If mean value is near to maximum value the whole block is considered. If mean value is in between minimum value and maximum value the threshold value is calculated. The minimum value is above 180 pixels in gray scale and the maximum value is above 255 pixels in gray scale. Once the threshold value is selected, the image with pixel value below the level of the threshold value is removed. The pixel value above the threshold level is considered.

2.2.4 Image Regeneration:

The image of 10 × 10 pixel value of the sub image is further combined into a single image and then compared with the original image [4]. The comparison of the gray image is done with the original RGB image. The zero pixel values of the gray scale images are replaced with RGB [2]. The pixel value of each component is 255. Now the background area as (uninfected area) and the object areas (infected area) are separated. Here, the background area becomes as white area. The area of bright lesion is calculated by counting the number of pixels in the extracted feature. The following technique is used to calculate the infected area. The infected areas (bright lesions) are divided by the whole image of the retina.

2.3 FEATURE EXTRACTION OF BRIGHT LESIONS

The feature extraction of the bright lesions of cotton wool spot are based on the color of the diabetic retinal image. If the pixel value of the red and green component is greater than 200 and the pixel value of the blue component is less than 80 then it is considered as cotton wool spot. It is a round or oval shape, pale yellow or white in color. The second feature of the bright lesion is the Large Plaque Hard Exudates (LPHE) based on white color. If the length of the bright lesions is greater than 40% length values then it is considered as LPHE. The third feature is hard exudates. If the length of the bright lesion is less than 40% length values then it is considered as hard exudates. Both hard exudates and LPHE are shiny, irregular shape.

3. DARK LESIONS

The threshold of the pixel vales between 10 and 50 is considered for the feature selection of the dark lesions. If the pixel value is less than 10 and greater than 50 such pixels are eliminated. The minimum threshold value is calculated by ignoring the pixel value of the image. Once the threshold value is identified microaneurosyms and hemorrhages are scanned based on the threshold value. Microaneurosyms are always like small dots. They occur at the nerve fiber ending. It has been identified whether it is micro aneurysm or vessel structure. If the size of the identified area is less than the diameter of the nerve the identified area is rejected.

3.1 IMAGE PREPROCESSING

The initial procedure in detecting dark lesions in a fundus image is image pre-processing. This stage enhances the features to be detected accurately in the successive stages. During image preprocessing the dark area of the image is eliminated using a fixed pixel threshold value less than 10. Since the area of interest is of a darker value, elimination is done by replacing the black pixel with white pixel. Once the background elimination is complete, the image is normalized by subtracting the difference of mean values of green component from the red component from a normalized value of 100. This step normalizes images to a red based image, by which accurate detection of red lesion is possible. Contrast of the normalized image is adjusted to enhance the red areas in the image and subdue the other components. After contrast adjustment in RGB, the green stream of the image is separated from the image. The green stream of the image carries all the information required for detecting the dark lesions. Therefore all the redundant information in the red and blue channel is eliminated. The green stream image is then subjected to grayscale illumination, during which process all the dark components become darker and bright components move towards the brighter area [1, 8]. This eliminates all redundant information which is not required for the detection procedure.

Similarly image normalization is used to extract retinal features of dark lesions such as Hemorrhages and Microaneurosyms. The input images may look like red based or yellow based images. In order to bring it into the same color orientation image normalization process is used [2, 9]. The input of the retinal image is having RGB components. The difference between Red and Green component is 100 pixels and above that it looks like red color image. If the difference between red and Green component is 70 pixels and below, then the image has a yellowish color.

3.2 MORPHOLOGICAL OPERATION

Morphological tools for extracting the features of interest in binary images have been used. The morphological area opening and closing operation has been used to enhance the image after preprocessing. Here morphological operation is used to detect and eliminate the vessels from the retinal images. Also, to separate the dark lesions of the micro aneurysms and hemorrhages [1, 3]. To check the nearby pixels morphological operation filtering is used. If pixel values are zero those pixels can be removed and the same pixel value is changed as one. Now the blood vessel at the nerve fiber ending is removed and features of the dark lesions can be extracted.

3.3 FEATURE EXTRACTION

Two main features are analyzed from the extracted red lesions. Based on the size of the extracted feature, the components can be categorized into micro aneurysms and hemorrhages. The size of the identified area is measured by the change in pixel value from white to red. If the size is less than 100 then it is micro aneurysms, and if above 100 pixel value then it is hemorrhages.

3.4 CLASSIFICATION OF NON PROLIFERATIVE DIABETIC RETINOPATHY (NPDR)

Classification of Non proliferative diabetic retinopathy is implemented based on set of rules. The rules used for classification of severity levels of NPDR and their definitions are stated in Table.1.

3.4.1 Rule Based Classification:

A rule based classifier is using a set of if, then, rules [1]. The following six rules are based on the variables numbers of Hard Exudates (HE), number of Cotton Wool Spots (CWS), number of LPHE (LPHE), number of Microaneurosyms (ANUE) and number of Hemorrhages (HEM) is present.

Rule 1: If (HE) V (CWS) V (LPHE) V (ANUE) V (HEM) = 0 then "Normal"

Rule 2: If (ANUE) = TRUE V (HE) V (CWS) V (LPHE) < 1% = 1 then "Mild NPDR"

Rule 3: If (ANUE) = TRUE V (HE) V (CWS) V (LPHE) > 1% ^ (HE) ≤ 5% = 1 then "Moderate NPDR"

Rule 4: If (ANUE) = TRUE V (HE) V (CWS) V (LPHE) > 5% ^ (HE) ≤ 20% = 1 then "Severe NPDR"

Rule 5: If (ANUE) = TRUE V (HE) V (CWS) V (LPHE) > 20% = 1 then "Very severe NPDR"

Rule 6: If (HEM) = TRUE = 1, then "Prolific DR".

The above sets of six rules are used for grading the abnormal retinal images.

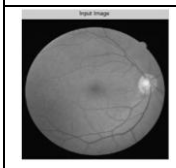
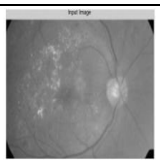
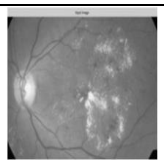
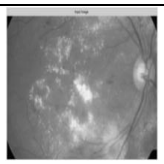
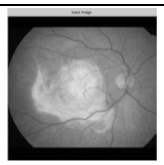
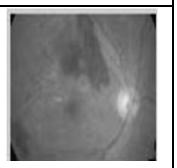
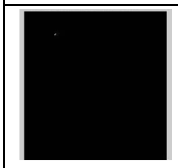
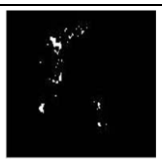
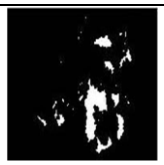
3.4.2 SVM Classification:

Support vector machines (SVMs) are a relatively new learning process influenced highly by advances in statistical learning theory and a sufficient increase in computer processing power in recent years. SVM is a useful technique for data classification. It is easier than other neural networks like back propagation network, Learning vector quantization. The Hyper plane optimally separates the vectors with maximal distance and reduced errors. To construct an optimal hyper plane, SVM employs an iterative training algorithm. It is used to minimize an error function and finds a linear separating hyper plane with the maximal margin in this higher dimensional space. Since it provides localized and finite responses across the entire range of the real x-axis. SVMs are effective in a wide range of bioinformatics problems. According to the features that are extracted, retina image can be classified as normal and abnormal diabetic retina. The false acceptance rate of SVM classifier is less than most well-known classifiers.

Table.1. Diabetic Retinopathy Disease Severity Scale used for the proposed study

Age Group	**26 – 65 years**		
Type Image	**Abnormal**		
No of Subjects	**90 Images**		
No. of stages	**Severity**	**Definition**	
Stage 0	Normal	None	0
Stage 1	Mild NPDR	Micro aneurysms	Aneurysms = True and Exudates < 1%
Stage 2	Moderate NPDR	Small patches of Exudates, Microaneurysms	Exudates > 1% and Exudates < 5%
Stage 3	Severe NPDR	Large Plaque of Exudates, Cotton wool Spots	Exudates or CWS > 5% and Exudates for CWS < 20% and Aneurysms = True
Stage 4	Very Severe NPDR	LPHE and CWS	Exudates or CWS > 20%
Stage 5	Prolific Diabetic Retinopathy	Hemorrhages	HEM = > 1

Table.2. Classified NPDR image

Normal	**Abnormal Mild NPDR**	**Abnormal Moderate**	**Abnormal Severe NPDR**	**Abnormal Very Severe**	**Abnormal Prolific NPDR**
None	Microaneurysm	HE, CWS	HE, CWS	LPHE	Hemorrhage
					
					

4. RESULTS AND DISCUSSION

In the present work, the features of the retinal images such as Microaneurosyms, Hemorrhages, hard exudates, cotton wool spots and LPHE have been extracted. The images have been obtained from two publicly available data bases of DRIVE and STARE for developing the decision support system. Then the system is validated considering the real time image obtained from Bejansingh Eye Hospital Nagercoil, India. The performance of various levels of the diabetic retinal image have been analyzed and compared by using extracted features. The performance of both bright and dark lesions have been analyzed and compared with those judged by the human experts. Classification of severity scale of NPDR and their levels are stated in Table.1. The Parameter number is sufficient to quantify the HE, CWS, LPHE, Microaneurysm and Hemorrhages

Table.2 shows the sample images for different grading of the diabetic retinopathy, with their features. From the above Table, it can be observed that if none of the features of the bright and dark lesions are present, then the image is normal. If in the features of the DR image microaneurysm is present then the image is graded as mild non proliferative. If the features of hard exudates and cotton wool sot are present then the image is graded as moderate non proliferative. The third stage of the DR image is graded as severe non proliferative by the presence of the features of hard exudates, cotton wool sot and large plaque hard exudates. The fourth stage of the DR image is graded as very severe non proliferative by means of presence of large plaque hard exudates. Final stage of the DR is proliferative if hemorrahages are present.

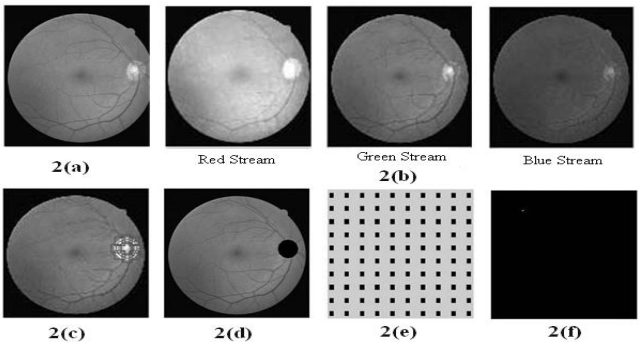


Fig.2. Sample results obtained for Normal retinal image
(a) Original image (b) Green Stream Extraction, (c) Optic Disc Identification, (d) Optic Disc Elimination (e) Block Processing (f) Classification results with decisions–Gray

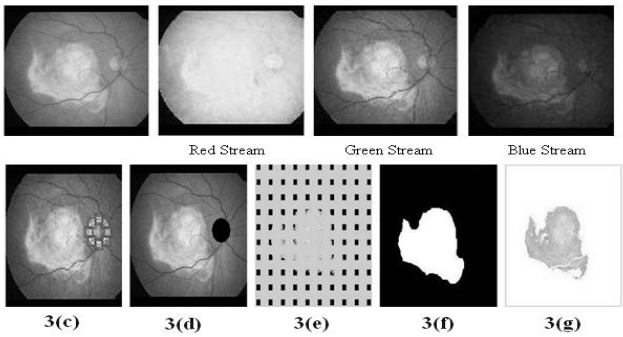


Fig.3. Sample results obtained for abnormal retinal image of Bright lesion (a) Original image (b) Green Stream Extraction, (c) Optic Disc Identification (d) Optic Disc Elimination (e) Block Processing (f) Classification results with decisions–Gray, (g) Classification results with decisions–RGB

The step by step process of the proposed method is described as follows. The proposed system considered for Normal and abnormal retinal image is shown in Figs.(2, 3 and 4). Fig.1 shows the sample results obtained for normal retinal image. Fig.2(a) shows the original image, Fig.2(b) shows the green stream extraction, Fig.2(c) shows the optic disc identification, Fig.2(d) shows optic disc elimination, Fig.2(e) shows the Block Processing and Fig.2(f) shows the classification results with decisions–Gray. Fig.3. Sample results obtained for abnormal retinal image of Bright lesion, Fig.3(a) shows Original image, Fig.3(b) shows green stream extraction, Fig.3(c) shows optic disc identification, Fig.3(d) shows optic disc elimination, Fig.3(e) shows block processing, Fig.3(f) shows classification results with decisions–Gray and Fig.3(g) show the classification results with decisions–RGB.

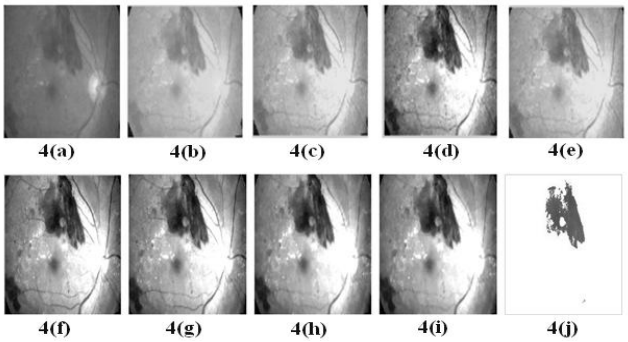


Fig.4. Sample results obtained for abnormal retinal image of Dark lesion (a) Original image (b) Brightness adjusted Image (c) Green Stream Extraction (d) Background Elimination (e)Gray Scale illumination (f) Morphological Operation–Area Opening, (g) Filtered Image (h) Morphological Operation–Area Closing, (i) Classification results with decisions–Gray (j)Classification results with decisions–RGB

Similarly Fig.4 shows the step by step procedure of the sampled results of an abnormal retinal image of dark lesions. Fig.4(a) shows Original image, Fig.4(b) shows brightness adjusted Image, Fig.4(c) shows green stream extraction, Fig.4(d) shows background elimination, Fig.4(e) shows Gray scale Illumination Fig.4(f) shows Morphological Operation–Area Opening, Fig.4(g) shows Filtered Image, Fig.4(h) shows Morphological Operation–Area Closing, Fig.4(i) shows Classification results with decisions–Gray and Fig.4(j) shows Classification results with decisions–RGB.

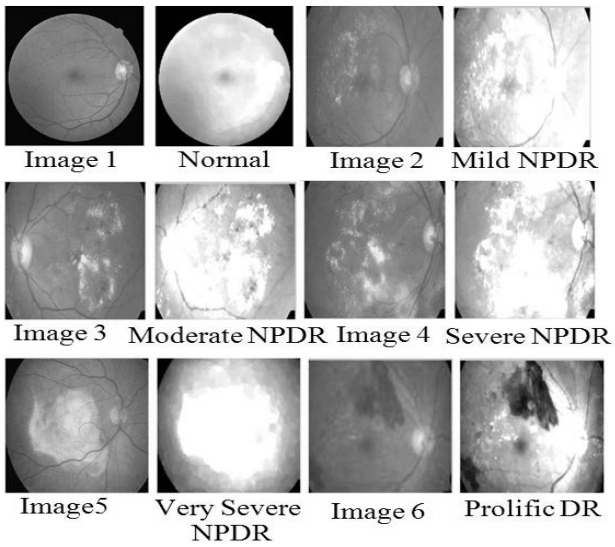


Fig.5. Original RGB Images and Classification results with decision for both Bright and Dark lesion

The above Fig.5 shows the classification results with decision obtained by using the proposed method. The performance of the proposed method is evaluated on the basis of four measures, namely True Positive (*TP*), True Negative (*TN*), False Positive (*FP*) and False Negative (*FN*). From these quantities, the sensitivity, specificity and Accuracy values were computed using equations.

TP represents a number of sensitivity. *TN* represents pixels of both bright and dark lesions correctly represented. This is also known as specificity [1, 2 and 6]. *FP* represents a number of non-bright lesion and dark lesion pixels which are detected wrongly as bright and dark lesion pixel [6]. *FN* represents a number of bright lesion and dark lesion pixels that were not detected.

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + TP} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

The performance measurements of *TP*, *TN*, *FP* and *FN*, sensitivity, specificity, accuracy and predictive values obtained using the proposed method on different diabetic retinal images of DRIVE, STARE and Began Singh Eye hospital, Nagercoil, India, data base images. Table.3 and Table.4 provide the estimated views of bright and dark lesions of the retinal images of abnormal images. The analysis has been done for 90 samples with age group varying 26 – 65. As a first step, measurements have been made on the objects of the bright lesions of the diabetic retinopathy. The same procedure has been repeated for the dark lesions of the diabetic retinopathy.

Table.3. The Bright Lesion detection results of diseased retinal images

Image ID	TP	FN	TN	FP	Sensitivity (%)	Specificity (%)	Accuracy (%)
Image 1	110547	4180	3198583	89098	96.3565682	97.2899439	97.25847
Image 2	272689	6871	3040461	56894	97.54220919	98.1631424	98.11174
Image 3	192763	5789	3104897	38934	97.08439099	98.7615747	98.66194
Image 4	255738	9567	3048392	18900	96.39396167	99.3838213	99.1458
Image 5	272694	11764	3040456	69058	95.86441584	97.7791385	97.61866
Image 6	267358	9835	3054743	45729	96.4519306	98.5250955	98.35496

Table.4. The Dark lesion detection results of diseased retinal images

Image ID	TP	FN	TN	FP	Sensitivity (%)	Specificity (%)	Accuracy (%)
Image 1	248411	21568	3070949	50253	92.0112305	98.3899472	97.88212
Image 2	13384	1765	3312056	35629	88.34906594	98.9357123	98.88802
Image 3	349021	47824	2978953	76395	87.94894732	97.4996302	96.40174
Image 4	452676	65902	2812056	45629	87.29178639	98.403288	96.69661
Image 5	17437	2598	3256396	68539	87.03269279	97.9386364	97.87331
Image 6	276431	35387	2987385	53756	88.6513928	98.232374	97.34136

From Table.3 and Table.4 the proposed method gives better sensitivity, specificity and accuracy for both bright and dark lesions. Graph illustrating the performance measurements.

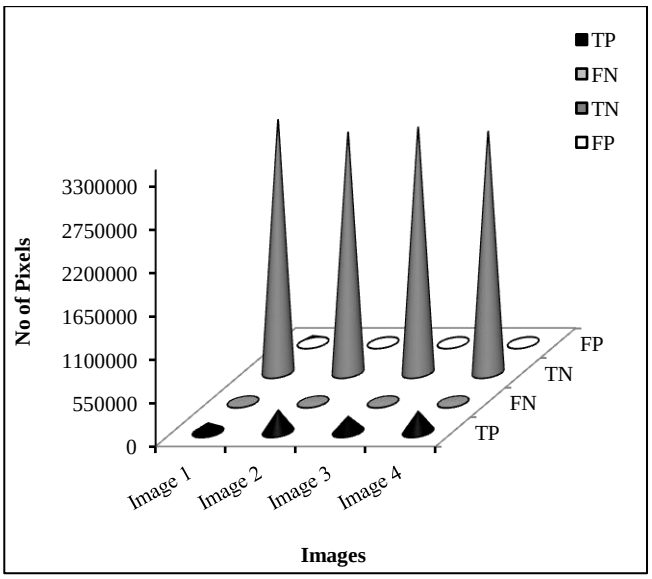


Fig.6. Performance measurement for bright lesions

It can be observed from Fig.6 that the size of the pixel rate of the detection of *TP* and *TN* values of bright lesions are very high with respect to *FP* and *FN*.

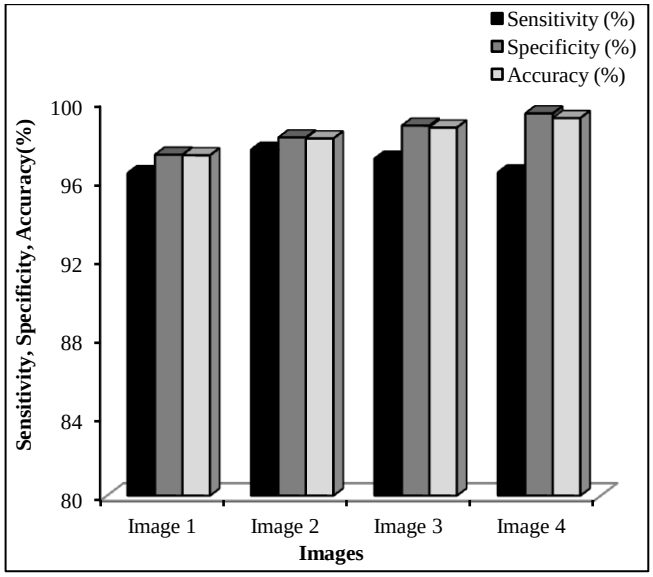


Fig.7. Sensitivity, specificity and the accuracy values on different images for bright lesions

From the Fig.7, it can be observed that the chart that the accuracy level of detecting bright lesions is very high for all samples tested. The mean accuracy values for tested images are 98.19%. The average sensitivity and specificity of the tested samples where 96.61% and 98.31% respectively.

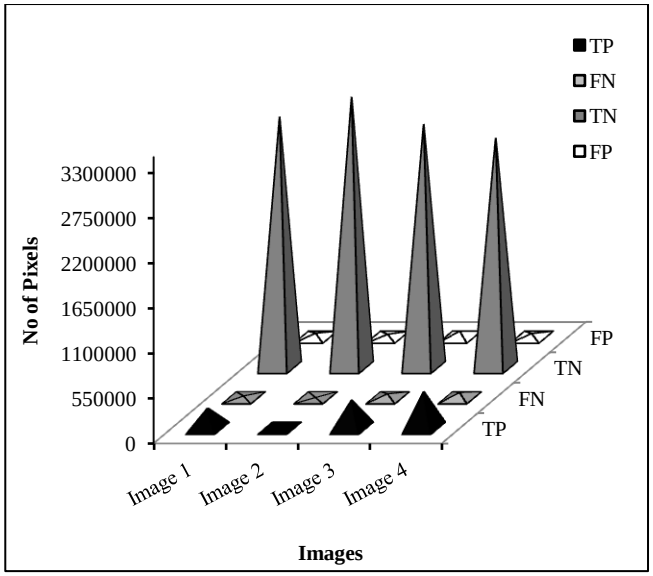


Fig.8. Performance measurements for dark lesions

From the Fig.8 it can be observed that the size of the pixel rate of the detection of *TP* and *TN* values of dark lesions are very high with respect to *FP* and *FN*.

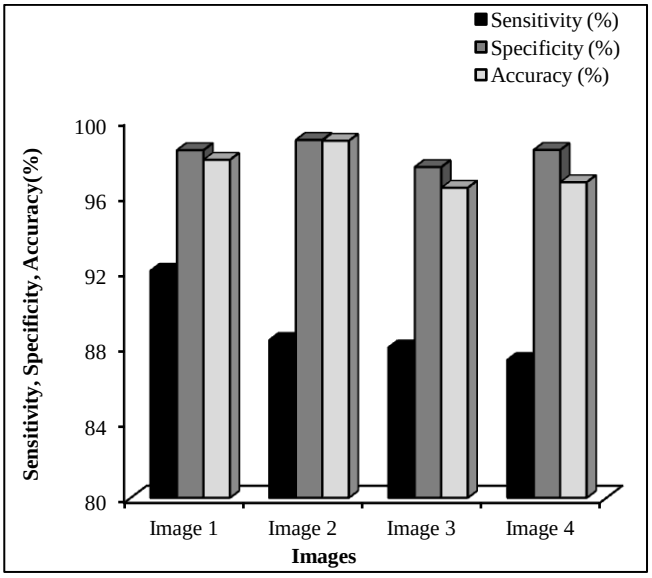


Fig.9. Sensitivity, Specificity and the Accuracy values on different images for dark lesions

From the Fig.9 it can be observed that the chart that the accuracy level of detecting dark lesions is very high for all samples tested. The mean accuracy values for tested images are 97.51%. The average sensitivity and specificity of the tested samples where 88.54% and 98.23% respectively.

Table.5. Performance Comparison with reference to image detected feature by ophthalmologist and proposed method

Image ID	Detected Features (Ophthalmologist)	Detected features (Proposed method)
Image 1	HE	HE
Image 2	HE, CWS	HE, CWS
Image 3	HE, CWS, LPHE	HE, CWS, LPHE
Image 4	ANUE, HE, CWS	ANUE, CWS
Image 5	ANUE, HE, CWS	ANUE, HE, CWS
Image 6	ANUE, HE, CWS, LPHE	ANUE, HE, CWS, LPHE
Image 7	HEAM	HEAM
Image 8	HEAM, LPHE	HEAM, LPHE
Image 9	HE, LPHE	HE, LPHE
Image 10	HE, CWS, LPHE	HE,CWS, LPHE

Table.5 provides the comparison of the proposed system with the ophthalmologists. It is found that the results obtained by the proposed method can be compared to those obtained by experts. The result analysis further reveals that 9 out of 10 fundus images are correctly detected by the proposed screening system. The correct sorting rate for this simulation gives 90% result, which indicates that only one image are wrongly interpreted. The misdetection may be due to poor image quality (as optic disc is not bright in some cases).

5. CONCLUSION

The computer aided diagnostic system to classify the retinal images using retinal network and rule based classifier has been developed and validated with various samples. The proposed method is capable of detecting the bright and dark lesions sharply with an average accuracy of 97.2% and 96.5%. 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. The proposed decision support frame work considers both bright and dark objects of fundus images for classification. The proposed work can detect disorders related to both dark and bright lesions of the retinal images of NPDR. 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 lesions in the retinal images to facilitate the ophthalmologists when they diagnose the retinal images.

ACKNOWLEDGEMENT

The authors are thankful to Dr. S.M. Bejansingh, Dr.(Mrs).Rooshitha Bejansingh, Bejansingh Eye Hospital, Nagercoil, India for providing required images and clinical suggestions. We are also grateful to Dr (Mrs.).Beena Asst Professor, Department of ophthalmology, Kanyakumari Government Medical College and Hospital, Nagercoil, India for the required clinical suggestions to carry out the present research.

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