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ORIGINAL PAPER

Automated Detection of Dark and Bright Lesions in Retinal Images for Early Detection of Diabetic Retinopathy

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Abstract There is an ever-increasing interest in the development of automatic medical diagnosis systems due to the advancement in computing technology and also to improve the service by medical community. The knowledge about health and disease is required for reliable and accurate medical diagnosis. Diabetic Retinopathy (DR) is one of the most common causes of blindness and it can be prevented if detected and treated early. DR has different signs and the most distinctive are microaneurysm and haemorrhage which are dark lesions and hard exudates and cotton wool spots which are bright lesions. Location and structure of blood vessels and optic disk play important role in accurate detection and classification of dark and bright lesions for early detection of DR. In this article, we propose a computer aided system for the early detection of DR. The article presents algorithms for retinal image preprocessing, blood vessel enhancement and segmentation and optic disk localization and detection which eventually lead to detection of different DR lesions using proposed hybrid fuzzy classifier. The developed methods are tested on four different publicly available databases. The presented methods are compared with recently published methods and the results show that presented methods outperform all others.

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Introduction

Diabetes is a disease that occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly [1]. Insulin is the hormone that regulates the level of sugar (glucose) in the blood. Diabetes can affect children and adults. Patients with diabetes are more likely to develop eye problems such as cataracts and glaucoma, but the disease's affect on the retina is the main threat to vision [2]. Most patients develop diabetic changes in the retina after approximately 20 years. The effect of diabetes on the eye is called DR [1].

Main features of retina are blood vessels, Optic Disc (OD) and macula (Fig. 1). Diabetes affects the blood vessels of the retina as time pases. Two main classes of DR are Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [1]. NPDR is the earliest phase of DR and also known as background diabetic retinopathy. In this phase, the blood vessels in the retina become weakened and leak, forming small, dot-like microaneurysm (MA) and hemorrhages (H) (Fig. 1). These leaking vessels often lead to swelling or edema in the retina and decreased vision. If the leakage contains fats and proteins along with water they cause yellow spots known as hard exudates (HE). In addition to this, small and thin blood vessel may close off causing some patches of retina deprived of blood supply. These small fluffy white patches in retina are called cotton wool spots (CWS) [1]. In

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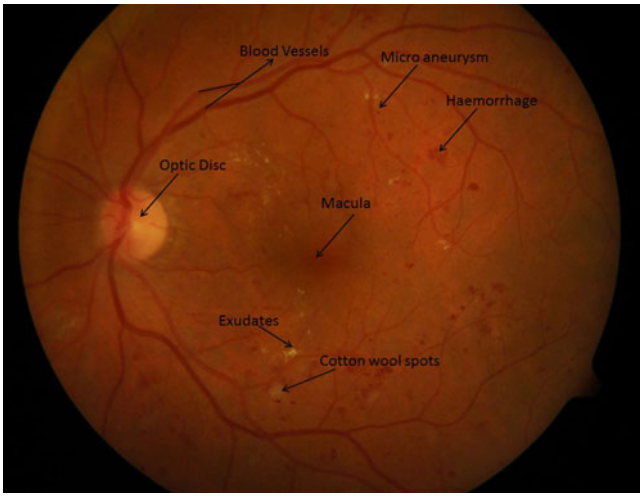

Fig. 1 Retinal image containing main features of retina and different NPDR lesions

PDR, circulation problems cause areas of the retina to become oxygen-deprived or ischemic. New, fragile, vessels develop as the circulatory system attempts to maintain adequate oxygen levels within the retina. This is called neovascularization. Unfortunately, these delicate vessels hemorrhage easily. Blood may leak into the retina and vitreous, causing spots or floaters, along with decreased vision. In the later phases of the disease, continued abnormal vessel growth and scar tissue may cause serious problems such as retinal detachment and glaucoma [2].

Digital information is acquired at different scales, quickly and efficiently by means of image processing techniques. So the algorithms can be developed for computer aided medical diagnosis based on image processing technology. Different techniques are used for acquiring retinal images. Most common are colored or monochromatic photography and angiography using fluorescent dyes [3]. In monochromatic photography, color filters are used to select light wavelengths that enhance the visibility of various fundus structures. Lighting using wavelengths close to the green region of the spectrum (known as red-free lighting) is frequently employed, as it leaves vessels, H and HE are more apparent. Angiographies, on the other hand, require the injection of a small amount of fluorescent dye into the patient, usually sodium fluorescein or indocyanine green. Fluorescence angiography permits recording of blood vessels and flow and also the detection of eventual leakages, of interest for diagnostic purposes. However, it is inadequate for screening programs, as angiogram can only be obtained by specialists in ophthalmology clinics, and is slightly invasive, presenting a certain risk of side effects to the patient. So an automated system for diabetic retinopathy screening is very helpful.

An automated assessment for pathologies of the retina initially requires the precise segmentation of the blood vessels and OD from the background, so that suitable lesion extraction and processing may be performed. Several methods have been developed for blood vessel and OD segmentation, but visual inspection and evaluation by receiver operating characteristic (ROC) analysis have shown that there is still room for improvement: human observers are significantly more accurate than the methods, which show flaws around the OD, in the presence of noise and in detection of the thinnest vessels.

This article consists of seven sections. The review of some relevant background material is given in section "Background & related work". Section "System overview" describes a brief overview of proposed system followed by preprocessing and main retinal feature extraction in Section "Preprocessing & retinal feature extraction". It explains background and noise removal, blood vessel enhancement and segmentation and OD localization and detection. The feature set formation and classification of dark and bright lesions are presented in Section "Lesion classification". The results are presented in Section "Experimental results", followed by conclusions in Section "Conclusion".

Background & related work

Preprocessing is done to extract retinal image from background and to enhance its quality by removing noisy areas. In automatic diagnosis of diabetic retinopathy, the processing of the surrounding background and noisy areas in retinal image is not necessary and consumes more processing time at all stages. Cutting or cropping out the region that contains the retinal image feature minimizes the number of operations on the retinal image. Noise in color retinal image is normally due to noise pixels and pixels whose color is distorted. Both seem to exist in regions where illumination has been inadequate. Since illumination is usually adequate in the center of the image, poor image quality regions are located near the edge of the retinal image. Regions with poor image quality may cause errors in abnormality detection. That is why they should be detected and removed before detection of abnormalities.

The detection and measurement of blood vessels can be used to quantify the severity of disease, as part of

the process of automated diagnosis of disease or in the assessment of the progression of therapy [18]. Retinal blood vessels have been shown to have measurable changes in diameter, branching angles, length or tortuosity, as a result of a disease. Thus a reliable method of vessel segmentation would be valuable for the early detection and characterization of changes due to such diseases [18]. Retinal vascular pattern facilitates the physicians for the purpose of diagnosing eye diseases, patient screening, and clinical study [12]. Inspection of blood vessels provides the information regarding pathological changes caused by ocular diseases including diabetes, hypertension, stroke and arteriosclerosis [16]. The hand mapping of retinal vasculature is a time consuming pro- cess that entails training and skill. Automated segmentation provides consistency and reduces the time required by a physician or a skilled technician for manual labeling [11]. Retinal vascular pattern is used for automatic generation of retinal maps for the treatment of age-related macular degeneration [9], extraction of characteristic points of the retinal vasculature for temporal or multimodal image registration [19], retinal image mosaic synthesis, identification of the optic disc position [20], and localization of the fovea [21]. The challenges faced in automated vessel detection include wide range of vessel widths, low contrast with respect with background and appearance of variety of structures in the image including the optic disc, the retinal boundary and other pathologies [22].

Various systems for automated classification of DR have been reported and most of them have given importance to preprocessing, blood vessel and OD segmentation. Standard contrast stretching techniques have been applied by [4] for preprocessing and noise reduction. The images are enhanced by the computer system using color intensity histograms. In [5–7] local and adaptive contrast enhancement methods are used for equalizing uneven illumination in the intensity channel of retinal images as a preprocessing step. Blood vessels are important for detection of different lesion such as microaneurysm, haemorrhage and neovascularization. Zhou et al. [8] proposed an algorithm which relied on a matched filtering approach coupled with a priori knowledge about retinal vessel properties to automatically detect the vessel boundaries, track the midline of the vessel, and extract useful parameters of clinical interest. A supervised classification based blood vessel segmentation technique was presented by Soares et al. [9]. A simple morphological opening and OTSU's thresholding based method was used by Nayak et al. [10]. In [11] ridge detection was used to form line elements and partition the image into patches belonging to each line element. Pixel features were then generated based on this representation to detect blood vessels. Chuadhuri et al. [12] proposed a technique using matched filters to emphasize blood vessels. An operator for feature extraction based on the optical and spatial properties of objects to be recognized was introduced. The optic disk generally appears as a bright circular or elliptic region on fundus image and it helps in detection of bright lesions. Any change in the shape, color, or depth of the optic disk is an indicator of various ophthalmic pathologies. Ahmed et al. [13] proposed a marker controlled watershed transform based technique for OD segmentation. In [14], an approximate location of the OD is estimated where the location of the OD is hypothesized by searching for regions of high intensity, diversity of gradient directions, and convergence of blood vessels. Sinthanayothin [15] located the position of the OD by finding the region with the highest local variation in the intensity. Hoover [16] utilized the geometric relationship between the OD and main blood vessels to identify the disc location. He described a method based on a fuzzy voting mechanism to find the OD location.

In this article, we propose a computer aided system for detection of DR. Main focus is on reliable segmentation of blood vessels and OD which will help in accurate classification of dark and bright lesions. Algorithms are tested and compared with already published techniques using four publicly available retinal image databases.

System overview

Computer assisted diagnosis for various diseases is very common now a days and medical imaging is playing a vital role in such computer assisted diagnosis. Image processing techniques can help in detecting dark and bright lesions from retinal image for diagnosis of DR. NPDR, also known as background DR, includes early sign of DR and can be diagnosed if detected accurately and in time. The proposed Digital Diabetic Retinopathy System (DDRS) uses a three stage procedure (Fig. 2). In first stage preprocessing is done to remove the background and noisy are from input retinal image. The blood vessel enhancement and segmentation followed by OD localization and detection is performed at second stage. In third stage, a hybrid fuzzy based classifier is used for detection of dark and bright lesions. DDRS uses blood vessel segmentation and OD for accurate detection and segmentation of different lesion for early detection and treatment of DR.

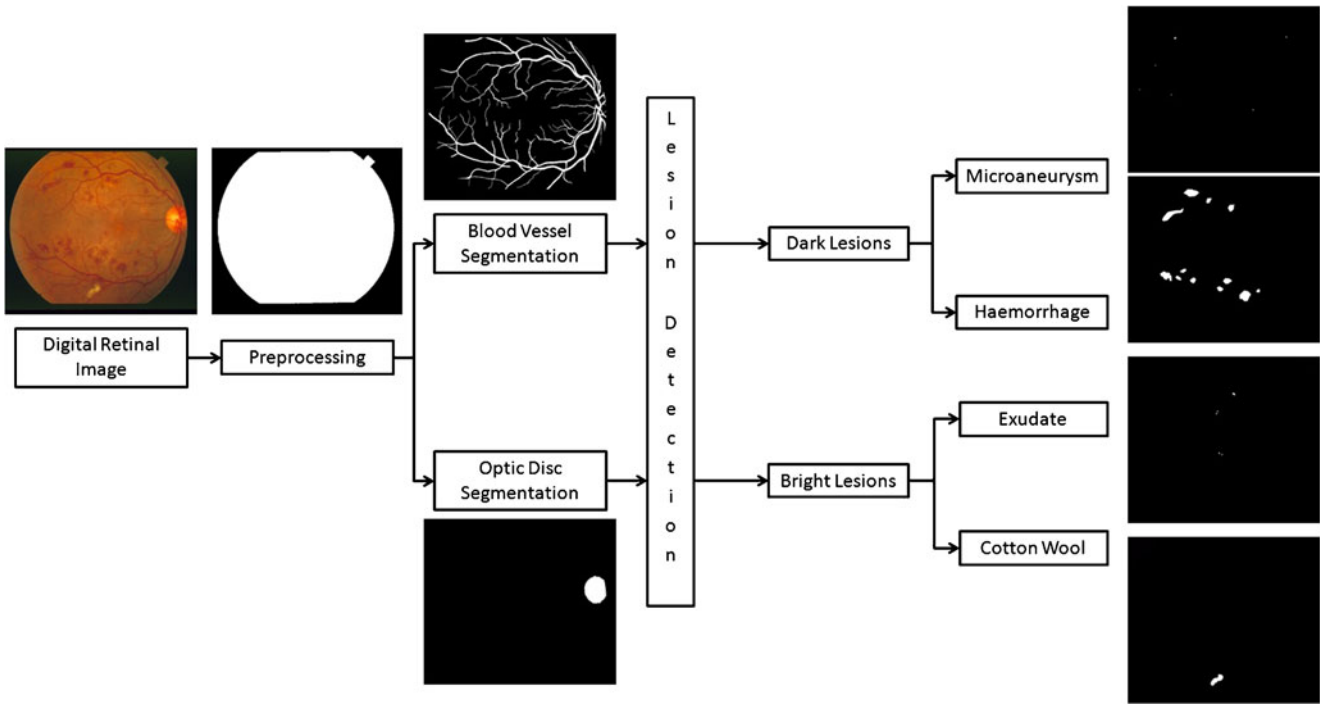

Fig. 2 Complete flow graph for proposed DDRS

Preprocessing & retinal feature extraction

Preprocessing

In preprocessing, We create binary masks for background and noisy areas. A mask is actually a combination of 1's and 0's, 1 is for true retinal image pixels and 0 is for background or noisy pixels. Background mask separates the original retinal image area from dark background and noise mask removes the noisy area from retinal image. Both masks are then combined and morphological operations are done on that combined mask to create the final mask. A color retinal image consists of a (semi) circular region of interest on a dark background. This dark background is initially never really black. It is important to distinguish between background and foreground, because feature extraction and abnormality detection algorithms only need to consider the foreground pixels. So it is necessary to remove the foreground from background. We have used local gradient mean and variance based method for background preprocessing [17]. It creates a binary background segmentation mask. In our technique, we create a binary noise mask which includes the noisy area and it is applied on retinal image to ensure not to process the noisy area in upcoming steps i.e. feature extraction and abnormality detection. In this technique, we convert RGB (Red, Green, and Blue) retinal image into HSI (Hue, Saturation, and Intensity) color space because firstly it is closer to the way a human experiences colors and secondly noise can be easily removed in HSI color space [24].

Mask that is formed by the combination of background mask and noise mask contains single pixel noise and edge pixels. Before applying final mask to retinal image, morphological operations i.e. morphological erosion and morphological dilation are applied to final mask. We have used square structuring element for erosion that removes all white single pixel noise from final mask but it increases the black single pixel noise. In order to remove the black pixel noise, same square structuring element is used for dilation. Final noise free mask is then applied on retinal image for its preprocessing segmentation. Figure 3 shows the original images and preprocessing masks for these images.

Vessel enhancement & segmentation

The problem with blood vessel segmentation is that the visibility of vascular pattern is usually not good especially for thin vessels. So, it is necessary to enhance the vascular pattern. Normally matched filters [16] and Gabor filters are used for this purpose but here we have used 2-D Gabor wavelet to enhance the vascular pattern and thin vessels [23]. Gabor wavelets

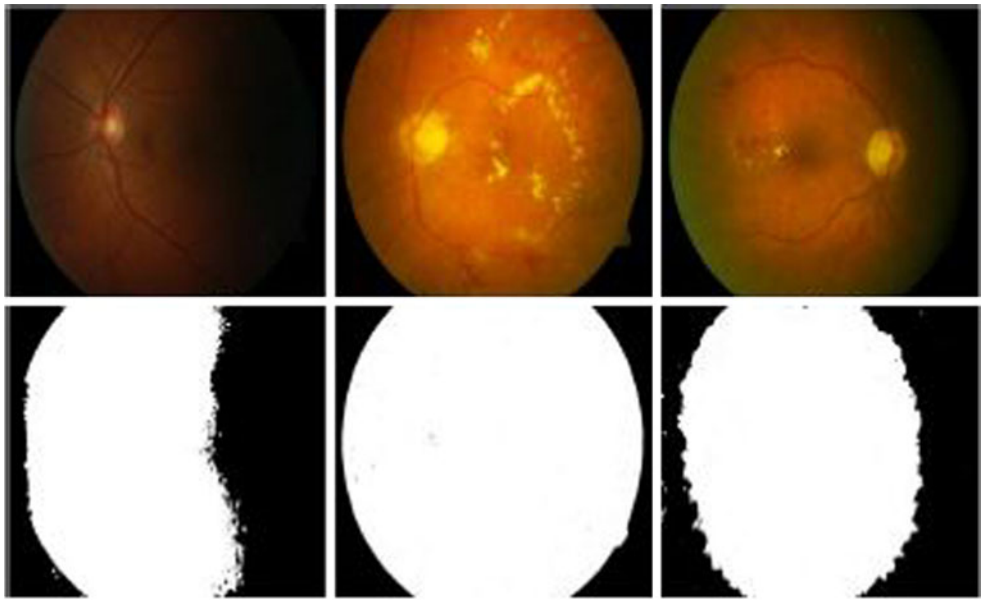

Fig. 3 Preprocessing: *row 1* original retinal images, *row 2* preprocessing mask to remove background and noise from original image

have directional selectiveness capability. They act as low level oriented edge discriminators and also filter out the background noise of the image. Since vessels have directional pattern so 2-D Gabor wavelet is best option due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies [23]. The 2-D Gabor wavelet which we have used is defined as

$$\psi_G(\mathbf{x}) = \exp(j\mathbf{k}_0\mathbf{x}) \exp\left(-\frac{1}{2}|\mathbf{A}\mathbf{x}|^2\right) \tag{1}$$

$$\hat{\psi}_G(\mathbf{x}) = (detB)^{1/2} \exp\left(-\frac{1}{2}(B(\mathbf{k}-\mathbf{k}_0)^2)\right) \tag{2}$$

where $\mathbf{k}_0 \in \mathcal{R}^2$ is a vector that defines the frequency of the complex exponential, $B = A^{-1}$ and $A = \begin{bmatrix} \epsilon^{-1/2} & 0 \\ 0 & 1 \end{bmatrix}$ with elongation $\epsilon \geq 1$ is a 2×2 positive definite diagonal matrix which defines the wavelet anisotropy and elongation of filter in any desired direction. For each pixel position and considered scale value, the Gabor wavelet transform $M_\psi(\mathbf{b}, a)$ is computed for θ spanning from 0° up to 165° at steps of 15° and the maximum is taken.

Wavelet based enhanced image has larger values where vessels are wide and prominent whereas low in case of thin vessels and edge pixels. So it is very difficult to find one optimal threshold value for accurate blood vessel segmentation without any supervised algorithm. In our multilayered thresholding technique, we apply different thresholds values iteratively and keep track of vessels in successive layers. At the start of segmentation, initial threshold value T is selected using histogram of wavelet image such that it only keeps those pixels in initial segmented image for which wavelet response is higher than T. The segmented image is then skeletonized using thinning morphological operator given in [24] as a result of which all vessels are now only one pixel wide. Vessels edges are then computed and filtered to eliminate all false edges. Then we lower the threshold iteratively and in each iteration keep all those vessels which are connected to the vessels segmented in previous iteration and stop the procedure when there is not any significant change in vessels during two consecutive iterations. Figure 4 shows the segmented blood vessels for different images from DRIVE and STARE databases.

Optic disc (OD) localization & detection

The OD generally appears as a bright circular or elliptic region on fundus image. The OD acts as a landmark and reference for extraction of other features, such as fovea. Its location helps to locate the fovea and its exclusion is essential in achieving robust bright lesion detection. We present a method for OD localization and segmentation. In OD localization, first original retinal image is preprocessed by averaging mask of size 31×31 (Eq. 3) in order to remove the background and lesions artifacts which can cause false localization and then maximum gray values from image histogram is detected because the gray values of OD are higher than the background values.

$$Z = \frac{1}{961} \sum_{i=1}^{961} F_i \tag{3}$$

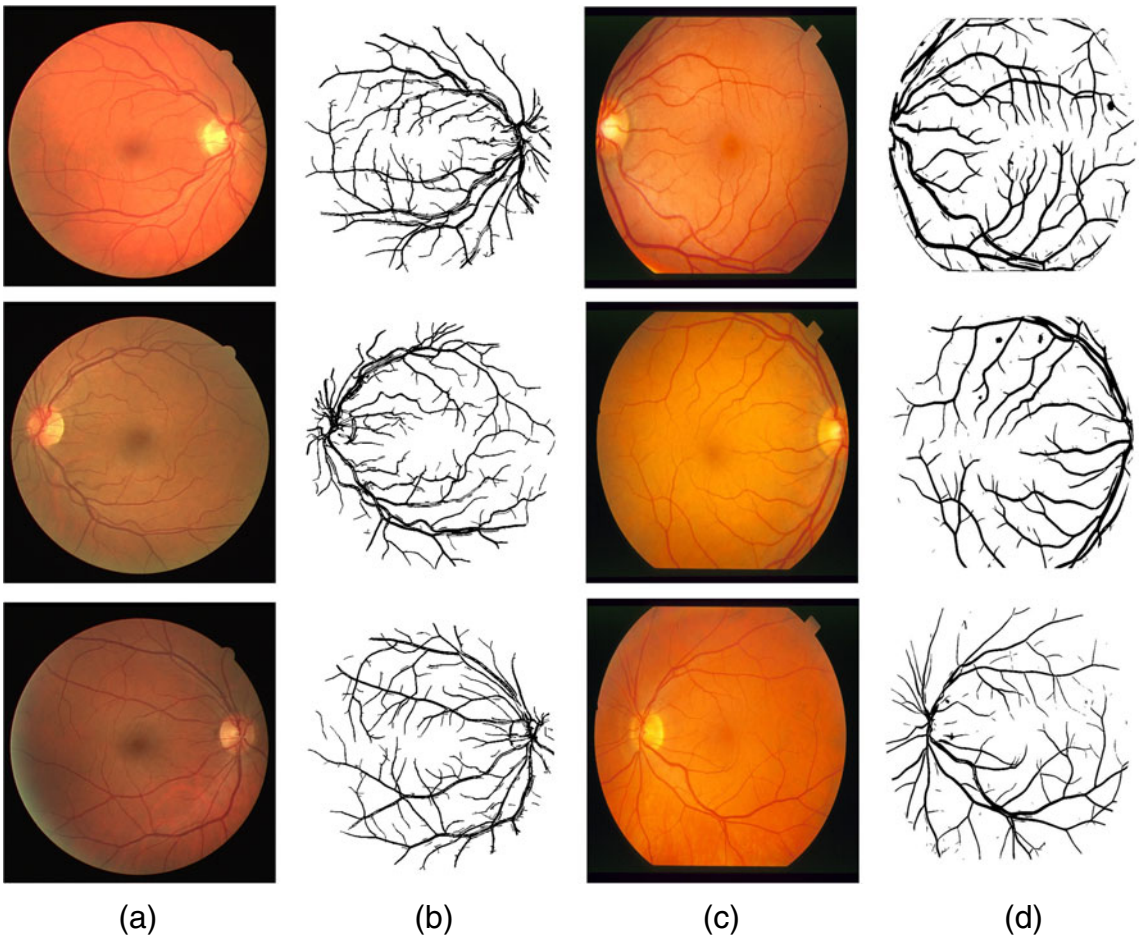

Fig. 4 Blood vessel segmentation: **a** original retinal images from DRIVE database, **b** segmented blood vessels, **c** original retinal images from STARE database, **d** segmented blood vessels

where F's are values of image gray levels and Z is the averaged image. Figure 5 shows the result of OD localization. After OD localization, region of interest (ROI) is defined to increase the performance of OD detection. After smoothing the size of ROI was set to 130×130. After extraction of ROI, Hough Transform (Eq. 4) is used to detect the OD boundary [25]. This transform consists of parameterized description of a feature at any given location in the original image space. It can be used for representing objects that can be parameterized mathematically as in our case OD has almost circular shape [29].

$$(x-a)^2 + (y-b)^2 = r^2 \tag{4}$$

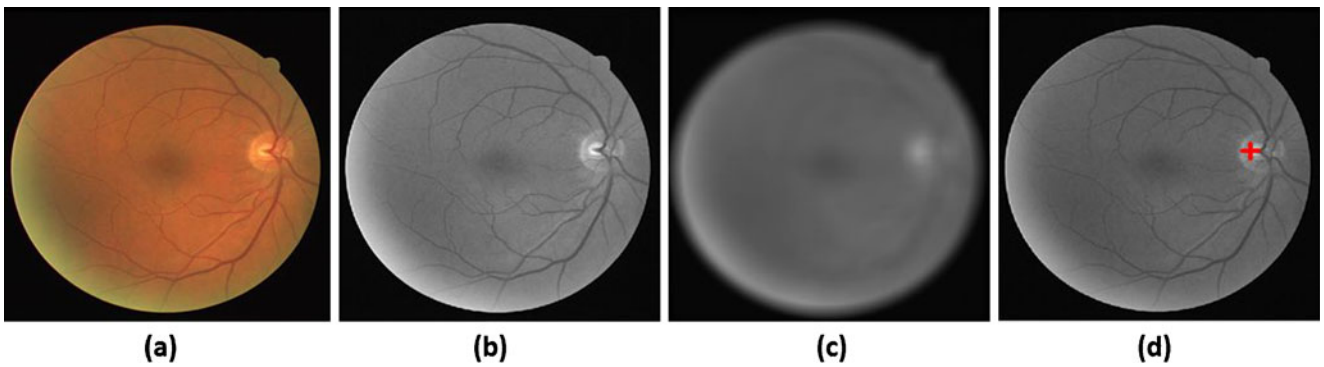

Fig. 5 OD localization: **a** original retinal image **b** green channel, **c** average filtered image, **d** localized OD

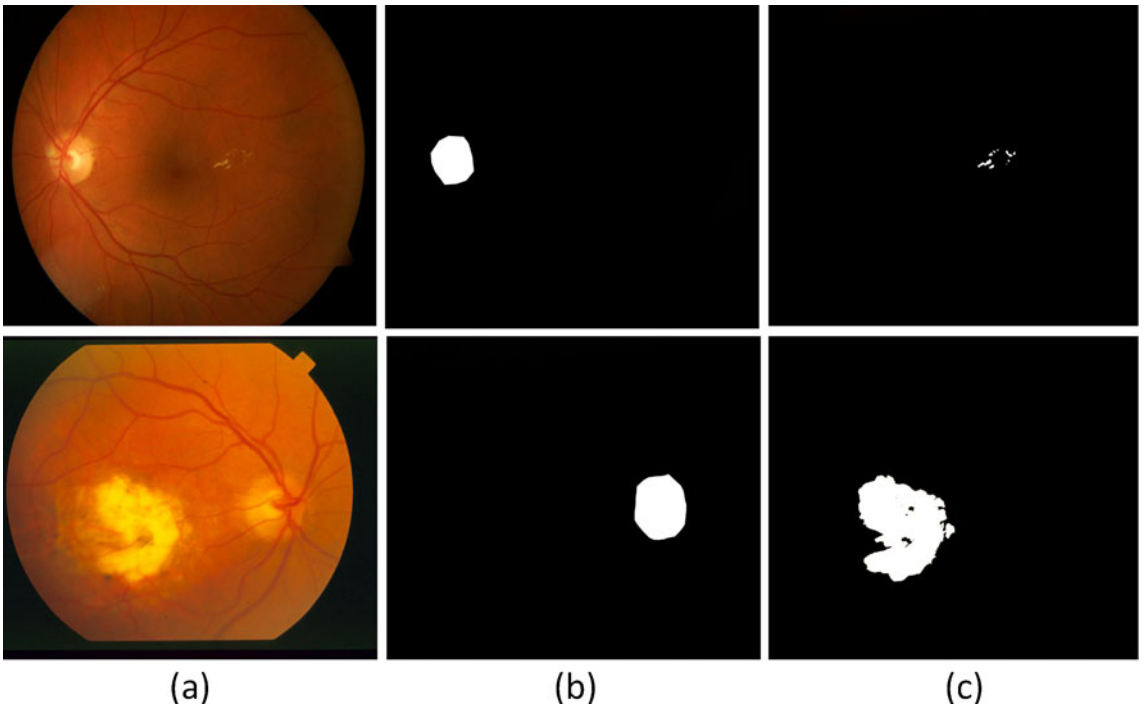

Fig. 6 OD and bright lesion segmentation: **a** original retinal image, **b** segmented OD, **c** segmented bright lesions

Where (a,b) is the coordinate of center of the circle that passes through (x,y) and r is its radius. Figure 6 shows OD segmentation even in the presence of bright lesions.

Lesion classification

Early detection of DR signs is very important for reliable diagnosis. Computerized classification of retinal images for detection of DR has been carried out from many different perspectives. However, due to similarity between early signs of DR and small blood vessels (capillaries), success of already presented algorithms have been very limited. Moreover OD and bright lesions show same properties. Therefore, classifier design needs to be less sensitive to blood vessels and OD. NPDR lesions appear with distinguishable properties such as color, size and shape etc. Microaneurysms (MA) are small in size and they appear in dark red color circles shape, Haemorrhages (H) are medium size dark red color dots. Exudates (HE) and Cotton Wool Spots(CWS) are of yellow and whitish colors respectively. Different properties for classification of dark and bright lesions are summarized in Table 1. Feature input vectors are formed using properties given in Table 1. In this paper, we made a feature vector $V = \{f_1, f_2, f_3, f_4, f_5, f_6\}$ for candidate lesions. The set which we have used for classification consist of following features:

Area (f_1), that is the count of number of pixels in each candidate lesion;
Mean Hue (f_2), *mean Saturation* (f_3) *and mean Value* (f_4) for each lesion are calculated in order to differentiate the lesions on basis of their color;
Eccentricity (f_5), which is the measure of circularness. For a circular region, eccentricity is always zero or near zero.
Mean gradient magnitude (f_6) for edge pixels is computed to differentiate between strong and blur edges.

For accurate classification, we propose two major innovations in the classification stage as compared to

Table 1 Classification properties for different NPDR lesions

Lesions	Color	Size	Shape	Edge	Class
Microaneurysm (MA)	Dark red	Small	Round	Clear	Dark lesion
Haemorrhage (H)	Dark red	Small-large	Dot-flame shaped	Clear-blur	Dark lesion
Exudate (HE)	Yellowish	Small-large	Irregular	Sharp	Bright lesion
Cotton wool spot (CWS)	Whitish	Small medium	Oval shaped	Blur	Bright lesion

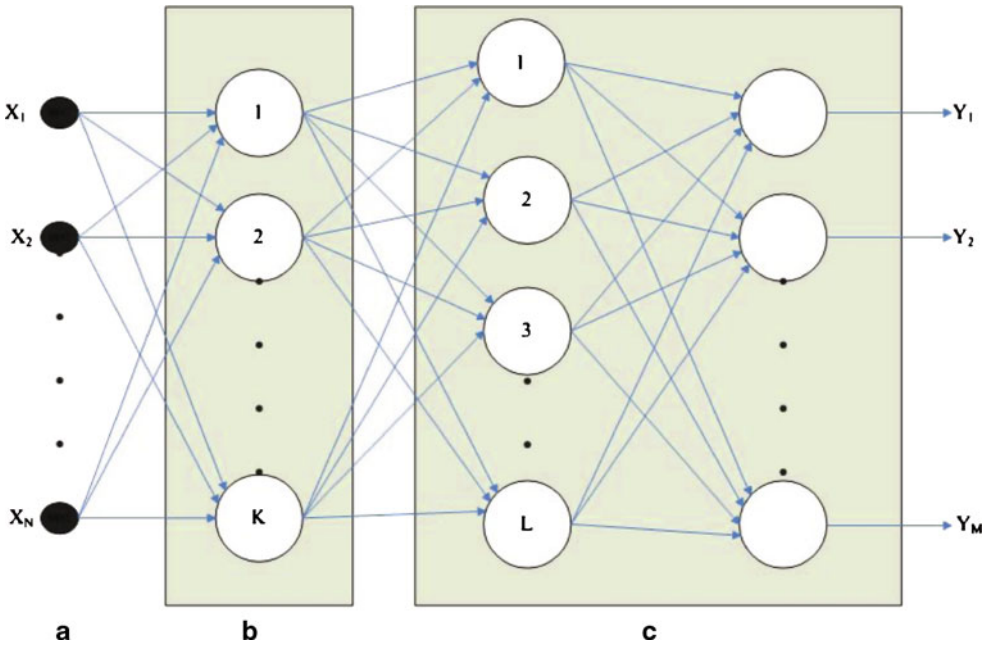

Fig. 7 Fuzzy hybrid neural classifiers: **a** input feature vector; **b** fuzzy self organizing layer; **c** MLP subnetwork

the conventional classifiers. First the classifier itself; we propose a fuzzy hybrid neural network which is composed of two subnetworks connected in cascade: the fuzzy self-organizing layer performing the pre-classification task followed by multilayer perceptron (MLP) working as the final classifier. The fuzzy self-organizing layer would be responsible for the detection of lesion pixels and grouping them into clusters with different membership values. Its outcome consists of clusters containing dark and bright lesions. On the basis of these membership values, the MLP network would classify the applied input vector, representing the extracted candidates to the appropriate class. Such fuzzy neural network solution would prove to be more tolerant to the noise and to the morphological variations of the lesions. Secondly, instead of using the original retinal images, we have used blood vessel and OD free fundus images. Figure 7 shows the fuzzy hybrid neural classifiers along with its different layers.

Experimental results

Data sets

A necessary tool for the reliable evaluation and comparison of medical image processing algorithms is a database including a selected set of high-quality medical images which are representatives of the diabetic retinopathy and have been verified by experts. In addition to the images, also information about the medical findings must be available. This information of findings is called the ground truth. An accurate algorithm should take an image as input, and output a result or description which is consistent with the ground truth. In this article four standard retinal image databases i.e. DRIVE, STARE, DiaretDB0 and DiaretDB1 are used.

The STARE-dataset was composed with the intention to create a difficult dataset. Only 31 images of healthy retinas are contained in this dataset. The other fifty retinal images exhibit a wide variety of lesions and other symptoms of diseases. This dataset was used by Hoover et al. [16] to test their method and to report quantitative results of the method. All these images were acquired using a TopCon TRV-50 fundus camera. Each of the images in the STARE-dataset has three color planes with 8 bits per plane. The sizes of the images are 700 × 605 with a circular 35° Field of view (FOV) chunked at the top and bottom of the field of view.

The DRIVE database has been established to facilitate comparative studies on segmentation of blood vessels in retinal images [11]. The photographs for the DRIVE database were obtained from a diabetic retinopathy screening program in the Netherlands. The screening population consisted of 400 diabetic subjects between 25–90 years of age. Forty photographs have been randomly selected, 33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy. Each image has been JPEG compressed. The images were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45° FOV. Each

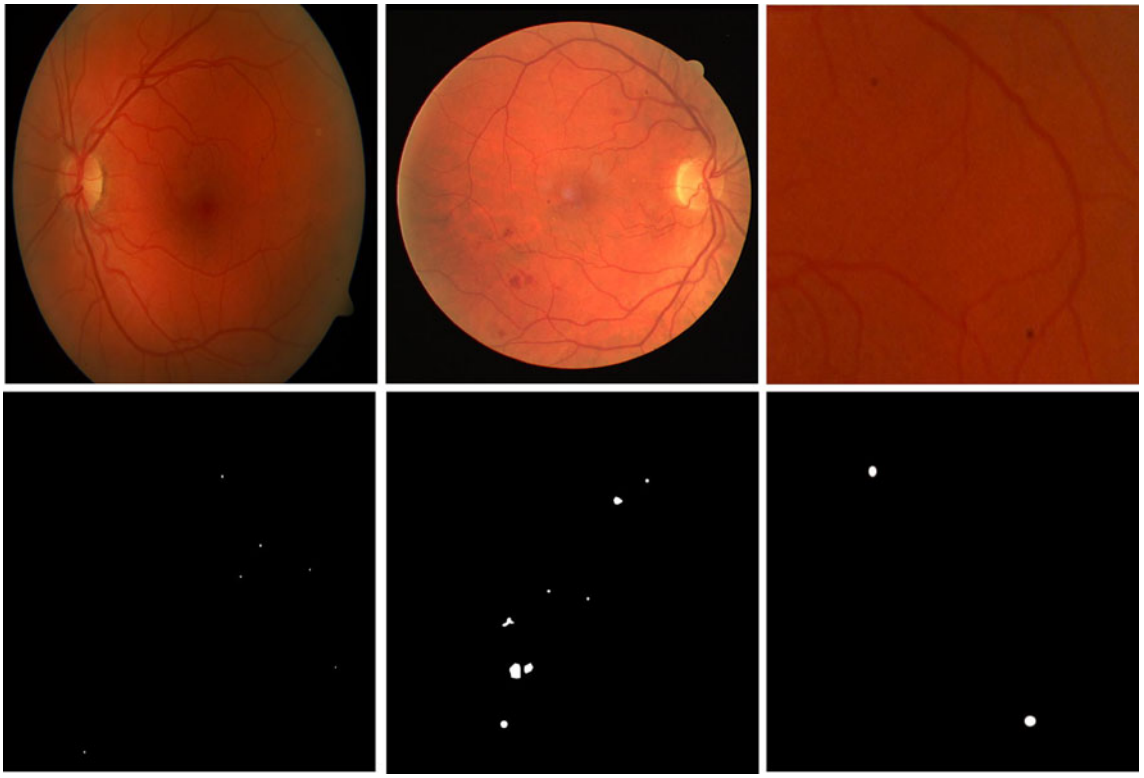

Fig. 8 Dark lesion segmentation: *first row* original retinal images; *second row* segmented dark lesions

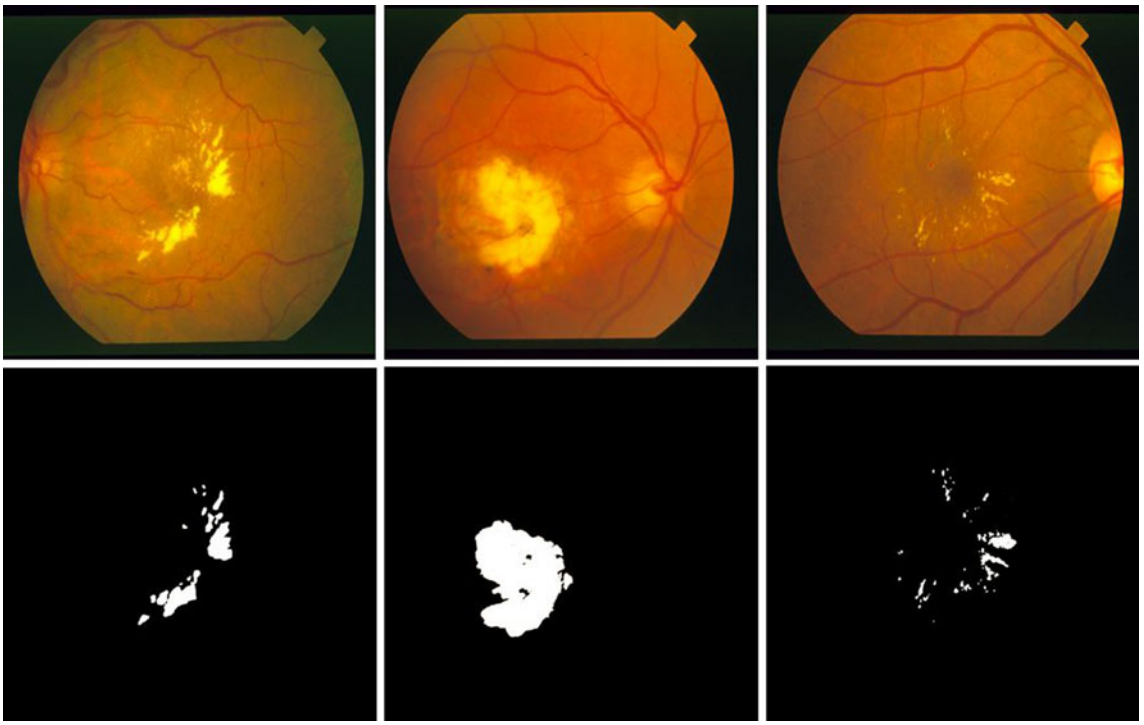

Fig. 9 Bright lesion segmentation: *first row* original retinal images; *second row* segmented bright lesions

Table 2 Performance of proposed DDRS

Databases	Preprocessing	Blood vessel	Optic disc	Dark lesions	Bright lesions
DRIVE	0.9982	0.9469	0.9917	0.9614	0.9623
STARE	0.9861	0.9502	0.9381	0.9598	0.9571
DiaretDB0	0.9769	0.9104	0.9692	0.9126	0.9389
DiaretDB1	0.9782	0.9214	0.9771	0.9160	0.9310

image was captured using 8 bits per color plane at 768 × 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels. For this database, the images have been cropped around the FOV.

Two more standard diabetic retinopathy retinal image databases are: diaretdb0 and diaretdb1. Diaretdb0 database contains 130 retinal images while diaretdb1 database contains 89 retinal images. These databases contain overall 219 retinal images with a resolution of 1500 × 1152 pixels and of different qualities in terms of noise and illumination. The diaretdb0 database consists of 130 color fundus images of which 20 are normal and 110 contain signs of the DR (MA, H, HE and CWS) [26]. The diaretdb1 database consists of 89 color fundus images of which 84 contain at least mild NPDR signs (MA's) of the DR, and 5 are considered as normal which do not contain any signs of the DR according to all experts who participated in the evaluation [27]. Images were captured using the same 50° FOV digital fundus camera with varying imaging settings. Figures 8 and 9 show the output of classifier highlighting dark and bright lesions from retinal images respectively.

Results

Accuracy is the fraction of pixels correctly classified and a complete step by step accuracy measure for proposed DDRS is shown in Table 2.

The manually segmented images by human observer are used as ground truth. The performance of proposed technique is measured using ROC curve which is a plot of true positive fraction versus false positive fraction.

Table 3 Blood vessel segmentation comparison results

Method	AUC (DRIVE)	AUC (STARE)
Chaudhuri et al.	0.9103	0.8987
Jiang et al.	0.9327	0.9298
Staal et al.	0.9520	0.9614
Soares et al.	0.9614	0.9671
Proposed	**0.9632**	**0.9706**

Table 4 Comparison of accuracy for dark lesions (MA & H) classification

Method	Accuracy (%)
Nayak et al. [10]	82.6
Sinthanayothin et al. [5]	91.8
Niemeijer et al. [30]	92.9
Proposed	**93.71**

In order to find the accuracy and area under the ROC curve (AUC), following parameters are calculated.

- TP (True Positive): Pixels that are graded as lesion pixels and they also belong to lesion in ground truth
- FP (False Positive): Pixels that are computed as lesion pixels but they are non lesion in ground truth
- TN (True Negative): Pixels that are computed as non lesion pixels and they are also non lesion in ground truth
- FN (False Negative): Pixels that are computed as non lesion pixels but they belong to lesion in ground truth

DRIVE and STARE databases contain manually segmented blood vessels and a number of blood vessel detection methods are tested on these databases. We compared the AUC of proposed technique with Chaudhuri et al. [12], Jiang et al. [19], Staal et al. [11] and Soares et al. [9] and comparison results are summarized in Table 3. An accurate system that fully agreed with ground truth should have $AUC = 1$.

The proposed DDRS achieved an accuracy of 95.97% for DRIVE and STARE databases as compared to 92.74% and 94.90% by Walter [28] and Reza[13] respectively and overall 94.7% for bright lesions (HE & CWS). The comparisons of proposed technique with already published methods are performed and summarized in Tables 4 and 5. Table 4 shows the comparison of accuracy for dark lesions detection whereas Table 5 shows the results for bright lesions detection.

A total of 20 images are selected from all four databases at random and for those images, a comparison between proposed method and ground truth for lesion

Table 5 Comparison of accuracy for bright lesions (HE & CWS) classification

Method	Accuracy (%)
Nayak et al. [10]	88.3
Walter et al. [28]	92.7
Reza et al. [13]	94.9
Proposed	**94.73**

Table 6 Performance comparison of lesion detection with ground truth

Images	Detected lesion (ground truth)	Detected lesions (proposed DDRS)
im0001	H, HE	H, HE
im0009	MA, H, HE, CWS	MA, H, HE, CWS
im0013	MA, H, HE, CWS	H, HE, CWS
im0022	–	–
im0031	CWS	CWS
im0139	MA, H, HE, CWS	MA, H, HE, CWS
03_test	MA, HE	MA, HE
06_test	–	–
14_test	MA, H	MA, H
17_test	HE	HE
image003	MA, H, HE, CWS	MA, HE, CWS
image009	MA, H, HE, CWS	MA, H, HE, CWS
image012	MA, HE	MA, HE
image025	MA, H, HE	MA, H, HE
image064	MA	MA
image074	MA, HE, CWS	MA, CWS
image108	H	H
image112	–	–
image118	MA, H	MA, H
image130	MA	MA

detection is given in Table 6. Table 6 shows that 3 out of 20 retinal images are wrongly classified (shown in bold font) and it is because of confusion between MA and thinnest vessels or capillaries.

Conclusion

In this article, we proposed a digital diabetic retinopathy system for early detection of diabetic retinopathy. NPDR consists of dark and bright lesions but it is difficult to classify them in the presence of blood vessels and optic disc. So it is good to segment them out prior to lesion detection. First step of proposed system is preprocessing. The objective of preprocessing is to separate the background and noisy area from the overall image to enhance the quality of acquired retinal image and to lower the processing time. After preprocessing, blood vessels are enhanced and segmented by using Gabor wavelet and multilayered thresholding respectively. Then we localized optic disk using average filter and thresholding and detected the optic disk boundary using Hough transform and edge detection. Once blood vessels and OD are segmented out, dark and bright lesions are detected using hybrid fuzzy classifier. Methods are tested using DRIVE, STARE, DiaretDB0 and DiaretDB1 databases and results show that proposed system gives comparable results and can be used in a computer aided system for accurate and early detection of diabetic retinopathy.

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