A Survey on Red Lesion Detection in Diabetic Retinopathy Affected Fundus Images

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Abstract—Diabetic Retinopathy is eye disease. Diabetic Retinopathy affects retina and further at severe stage it may cause vision loss. Diabetic Retinopathy is possible in long term diabetic patients. Diabetic retinopathy is due to increased sugar level in the retinal capillaries. The fundus images are used to analyze the red lesion. Small red lesions spots are micro aneurysms and large are hemorrhages. Early red lesion detection can help to avoid blindness. Automatic detection of red lesions in retinal images can help in early identification and screening of retinopathy diseases. Algorithm is tested using performance metrics such as Sensitivity & Specificity.

Keywords—diabetic retinopathy, screening, automatic detection, fundus images, blood vessels, optic disk, red lesions, microaneurysms, hemorrhages, false positive elimination.

I. INTRODUCTION

Diabetic Retinopathy is diseases of eye can cause blindness. Blood vessels(BVs) leaks protein and blood causes DR. This disease is mainly caused due to increased sugar level in blood that damages the small BVs of the retina.[4]

Many people are suffering from diabetic retinopathy (DR). If this disease is found at an early stage, then can be detected and prevented from turning into blindness. However, it has been seen that people are becoming blind due to DR is increasing day by day. Fundus camera gives digital retinal images which are used to diagnose DR.

Ophthalmologists has to examine the excessively large number of fundus images. Fundus images free from DR in a screening is typically over 90%. Therefore, an automated system first that finds out the images with suspicious signs for DR. Only those images are examined by ophthalmologists to improve efficiency.[3] Automated methods are prescreening systems. Diabetic retinopathy can be classified into two groups, early stage of DR is non-proliferative diabetic retinopathy and further is proliferative diabetic retinopathy. This can cause blindness in diabetic patients. NPDR is again classified as mild & moderate[1]. For disease classification into different levels of severity classifiers are used.

The purpose of this paper is to give literature survey in the field of red lesion detection, for researchers with appropriate way to get retinal images, to provide information about the available methodologies used for detection of red lesion and to comparing the results.

II. METHODOLOGIES USED IN RED LESION DETECTION

Red lesion detection methods can be divided into two main stages. First is red lesion candidate extraction and second is classification. Image preprocessing is first stage to reduce noise and improve contrast. Further red area in the image are extracted and segmented to find out the candidate of red lesion. Blood vessels are extracted using segmentation algorithms from the candidates to reduce false detection. Then features are extracted and selected and used to detect red lesion. The classification algorithm is applied to classify the red lesion or non red lesion. The following sections gives the researches based on their main methodologies. Figure 1 shows the flow of process.

A. Image Processing

Mane et al. [1] used green channel and histogram equalization for contrast enhancement.

Mane et al. [2] used green channel and Adaptive histogram equalization for contrast enhancement.

Kumar et al. [3] produced background image by median filtering green plane image. Then intensity variations correction are obtained by subtracting background image from green plane image.

Lachure et al. [4] produced HIS color model from RGB image. To smooth the quality of image Hybrid median filter is used. This reduces the noise due to thinness and thickness of boundaries of features. This also gives better edge corner prevention. Finally CLAHE is performed for contrast enhancement between red lesion and background.
Figure I. The processes of Red Lesion detection

Adarsh et al. [5] used green channel plane and for contrast enhancement CLAHE is performed.

B. Extraction of Retinal Blood Vessels and Candidate red lesion Detection

Mane et al. [1] used convolullon for enhancement of the red lesion in original image. For this purpose 2D matched filter kernels are used. After extracting the enhanced red lesion segments, the Local Entropy thresholding is used for thresholding operation.

For enhancement of blood vessels Mane et al. [2] implemented advanced matched filtering and for accurate segmentation of blood vessels. Local entropy thresholding is used for automatic and precise selection of threshold. Then all candidate lesions are extracted by series of morphological operations. Classifier is trained using extracted features.

Kumar et al. [3] Morphological top-hat transformation is used for discriminating between rounded, disconnected red lesions and the extended vasculature. Morphological top-hat transformation is morphological opening by linear SE at different orientations.18 S.E. with radial resolution 100 are used. Length of SE is greater than largest red lesion. Highest intensity of each pixel contained in all 18 images gives map of vasculature. Vasculature map was subtracted from shade corrected image gives red lesions.

For detection of red lesions, it need contrast enhancement between background and red lesions in lesion image. A matched filter is employed for contrast enhancement. Matched filtered image contains red lesions with sharpened edges. To produce binary image, match filtered image is thresholded.

Non red lesion candidates may be detected as false positives in the binary thresholding. A three stage elimination strategy for FPs. Removal of non red lesions [FPs] elsewhere, on the blood vessel, in the optic disc region.

Lachure et al. [4] performed following steps for candidate extraction and blood vessel detection

1) Optical Disc Elimination :- Optical disc have similar intensity value like Exudates, should be removed. Canny edge detection is employed for detection of BVs and optical disc. Then mask image is created by logical black & white function and then inverting image and further subtracted from the canny edge detected image. This eliminates Optical disc.

2) Blood Vessels Extraction and Removal:- Disk Shaped Structural element is used. Dilation is used to detect boundaries of object. Erosion operator is used to remove completely blood vessels from images.

3) Identify Exudates:- Exudate is identified using closing operation.

4) Detection of micro-aneurysms:- For detection of micro-aneurysms image invert method is used and followed by morphological opening operation

Adarsh et al. [5] used following steps blood vessel for exudates and micro-aneurysms detection.

a) Blood vessel detection:-

CLAHE applied image of green channel image one time gives (P1)

\((P2) = \Phi B8 (P1)\) \hspace{1cm} (1)

Where \((\Phi)\) is ball-shaped structuring element morphological opening operator with fixed radius eight (B8).

Optic disk removed image (P3) is obtained by following equation.

\((P3) = (P1) - (P2)\) \hspace{1cm} (2)

To reduce noise on (P3) connected component analysis is used and gives blood vessel image(BV) (P4).CLAHE is applied 3 times and also thresholding to give second BV image (P5).

Let (P6) gray scale image obtained from RGB fundus image. Optic disc is obtained from maximum intensity pixels in (P6). A mask of mask of disc is and added to (P5). The mask radius is 90.

Further AND operation of (P4) and (P5) for comparing them to remove noises. Using canny edge detection border having circular shape is created and removed and then morphological opening operation gives blood vessel image.

b) Exudates Detection:-

\((P7) = \Psi_{B10} (P6)\) \hspace{1cm} (3)

Where \(\Psi = \text{Morphological closing operator}\)

\(B10 = \text{SE of fixed size radius ten}\)

Further for exudate area detection column wise neighborhood operation is used. Temporary matrix (P8) is created by rearranging each M x N block of (P7) into a column. This operation gives only the border, exudates and the optic disc.

The exudates region is detected and then the border and
optical disk are subtracted to give image (P9). Then the exudates region is expanded using operator (Ψ) and the noise persisting is removed after column filtering to give (P10).

CLAHE is applied on (P6) once again. For identifying non-exudates, threshold value of 0.85 is used gives (P11). Further AND operation of (P10) and (P11) for comparing so to detect the exudates.

c) Microaneurysms Detection

Canny edge detection on CLAHE applied image of green channel image (P1) to give image (P12). Further circular border obtained after canny edge detection is subtracted from (P12). Also background pixel filling gives (P13). Primary image (P14) contains microaneurysms is formed as follows.

\[(P14) = (P13) − (P12) \tag{4}\]

Remaining large area found is then subtracted from (P14) for removing the noise with large area which gives (P15). Simultaneously the green channel image is three times contrast enhanced and thresholded using 0.7 as threshold gives (P16). Further AND operation performed on (P15) and (P16) for comparing so to obtain the exudates free image (P17). Then similarly green channel image is contrast enhanced two times and then thresholding using 0.3 as threshold to get (P18). Further AND operation performed on (P17) and (P18) for comparing so to get the image (P19) free from vasculature. Finally microaneurysms are obtained by subtracting the optical disk.

C. Feature Extraction and Classification

For separation of Red lesion and non-red lesion, Mane et al. [1] used four filters shown below.
1. Area
2. The aspect ratio
3. The mean
4. Compactness

For each of tentative red lesion, Mane et al. [2] decided 11 features. These features include area, aspect ratio, perimeter, major axis length, minor axis length, eccentricity, mean intensity, standard deviation, compactness, roundness and equivalent diameter of that object.

SVM classifier is used for classification. Classifier is trained images which are obtained from DIARETDB I database. SVM constructs a hyper-plane in feature space classify the present data. It is s class 1 or O. Class 1 is for true lesions and class 0 is for non-lesions. If classifier's output is 1 then input region is the true red lesion. All such true red lesions in the output image are counted. Finally all the true red lesion present in output image are remapped in original input image.

Lachure et al. [4] extracted features as
1) Entropy:- Entropy is a statistical measure of randomness of texture of the input retinal image.
2) Contrast:- Enhances the contrast of an retinal image.
3) Energy:- Energy is a measure of “information” when formulating an operation under a probability framework.
4) Homogeneity


The purpose of selecting these features to reducing noise and enhance accuracy of the result of classifier.

Multiclass SVM Classifier is used here. There are two main types of multiclass SVM a) “One-against-all” and b) “one-against-one”. “One-against-all” is implemented here with no. of binary classifiers. Each binary classifier is trained to isolate one class from the other remaining all classes.

III. PERFORMANCE EVALUATION

Performance metrics such as sensitivity, specificity are calculated to evaluate the system.

Sensitivity is amount of true positives correctly classified by system. Specificity is amount of true negatives correctly classified by system. The equations are given below:

\[
\text{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100\% \tag{5}
\]
\[
\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100\% \tag{6}
\]

Where

True Positive (TP): Red lesion correctly identified as red lesion.

True Negative (TN): Nonred lesion correctly identified as nonred lesion.

False Positive (FP): Nonred lesion incorrectly identified as red lesion.

False Negative (FN): Red lesion incorrectly identified as nonred lesion.

Following table 1 shows comparison of five methods based on sensitivity and specificity.

<table>
<thead>
<tr>
<th>Author</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mane et al. [1]</td>
<td>87.71</td>
<td>94.62</td>
</tr>
<tr>
<td>Mane et al. [2]</td>
<td>96.42</td>
<td>100</td>
</tr>
<tr>
<td>Kumar et al. [3]</td>
<td>95.6</td>
<td>93.2</td>
</tr>
<tr>
<td>Lachure et al. [4]</td>
<td>90</td>
<td>100</td>
</tr>
<tr>
<td>Adarsh et al. [5]</td>
<td>90.6</td>
<td>93.6</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

The automatic red lesion detection is difficult job. It is not easy to separate out the red lesions from background variations because of red lesion have low contrast. There may be false positives detection which are other dark areas in the image such as the blood vessels, fovea. Red lesions are of different size and usually they are so
small. There is no any standard database available to classify red lesion by shape. The most false detection is because of the BVs are so close or crossing with red lesion. So the effective red lesion detection methodology is needed. This paper reviews some available methods which give a idea of the field. Using this work, a link can be provided to start with the problem and can make better and more optimal algorithms.

REFERENCES


[2] Vijay M Mane, Ramish B Kawadiwale, Prof. (Dr.) D. V. Jadhav, “Detection of Red Lesions in Diabetic Retinopathy Affected Fundus Images”

[3] Sharath Kumar P N, Rajesh Kumar R, Dr. Anuja Sathar, Dr. Sahasranamam V ,“Automatic Detection of Red Lesions in Digital Color Retinal Images” 2014 International Conference on Contemporary Computing and Informatics (IC3I)

[4] Dr. Jaykurnar Lachure, Mr. A.V. Deorankar, Mr. Sagar Lachure, Miss. Swati Gupta, Mr. Romit Jadhav, “Diabetic Retinopathy using Morphological Operations and Machine Learning” 2015 IEEE International Advance Computing Conference (IACC)