Indian Journal of Science and Technology, Vol 9(25), DOI: 10.17485/ijst/2016/v9i25/90183, July 2016
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Fundus Image Screening for Diabetic Retinopathy

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Abstract

The proposed system aims in diagnosing Diabetic Retinopathy (DR), a snag in patients with Diabetes for prolonged periods. MinIMaS algorithm is primarily used for background Extraction and Gaussian Mixture Model (GMM) is used for grouping of lesions. The amount of false positives are minimized by the selection of feature vectors used for classification. The proposed system achieves sensitivity of 89% for grouping of bright lesion and sensitivity of 82% for classifying bright lesion which when compared to existing system (KNN classifier) gives a higher sensitivity value. Similarly MinIMaS algorithm provides 91% accurate results when compared to the existing Haar based wavelet transform (70%) and Highest Average Variation (65%). System aids in detecting severity of Diabetic Retinopthy with improved accuracy for timely treatment of patients.

Keywords: Diabetic Retinopathy, Fundus, Lesion, Screening

1. Introduction

Diabetic Retinopathy is an eye disease which have an effect on the retina of persons with prolonged diabetes which if untreated can cause blindness. Diabetic Retinopathy causes 2 major problems, one thing is insufficient blood supply that can cause shortage of oxygen in retina, which in turn leads to the formation of new blood vessels named as Neovascularization[1], other being leakage from tissues and blood vessels which causes inflammation in the central part of retina termed as Macular Edema[2]. DR is characterized by group of lesions such as exudates, microaneurysms and haemorrhages. Image processing of fundus images play a vital role in the diagnoses of DR. Various ways in which it contribute includes enhancement of image, mass screening (pathology detection) and monitoring (feature detection). Pathologies of the disease are shown in Figure 1 and described as follows:

1.1 Exudates

Exudates can be both cotton wool spots/soft exudates and hard exudates. Cotton wool spots are fluffy white patches seen in the retina which are formed by damage to nerve fibers and also of the hoarding of the axoplasmic material within the bounds of the nerve fiber layer. Hard Exudates are seen as yellow dots in retina formed by disintegration of lipid products that are left to the far side after localized edema rectifies.

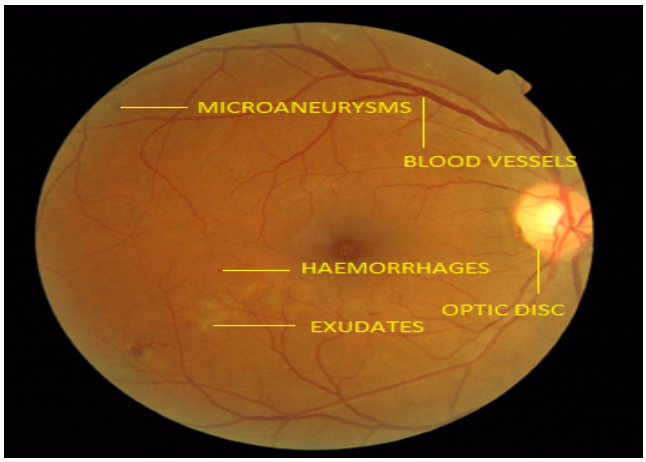

Figure 1. Retinal image with lesions.

1.2 Microaneurysms and Haemorrhages

Aneurysm is the uncontrolled localized swelling of the wall of an artery, microaneurysms are seen in the retina of the eye of DR victims and these miniature aneurysms can discharge blood by rupturing. Hemorrhage is the leakage

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of blood from ruptured vessel in the retina.

1.3 Disease Progression

The premature symptom of DR is microaneurysms appearing as dark red spots in retina, haemorrhages arise when microaneurysms rupture. Yellow colored lesions, hard exudates appear due to fluid escaping into retinal surface from capillaries or from microaneurysms. Cotton wool spots are the blood vessel blockage of the nerve fiber layer. DR is an intensifying disease, the first stage during in which the bruises/lesions appear is NPDR (Non Proliferative Diabetic Retinopathy) and increases as the disease progresses.

2. Literature Review

Diabetic Retinopathy is diagnosed by means of Clutter Rejection methodology[3], in which two rejection stages are involved. Rejection Stage 1 uses anisotropic filters, Inverted Gaussians, Scaled difference of Gaussians in identifying clutters arise due to haemorrhages, candidates on vessels and junctions. Clutters formed of image noise, poor image resolution are eliminated in Rejection Stage 2 on the basis of distance, correlation and level cut features. Significance of the method is that only true microaneurysms are retained in cascading rejectors and the false positives are totally absent.

Curvature[4] based algorithm which measures the Tortuosity, a curvature indicator of inflexion, the curve changing from convex to concave or vice versa are analyzed using methods of curvature. Advantage of the system is that it poses low computational complexity but the method does not exhibit magnitude in opposition to curvature and the vessel network tortuosity is dependent on the state of the arteries.

Diabetic Retinopathy can be diagnosed by means of soft computing neural networks[5], Efficient Local Binary Pattern (ELBP) is used for segmenting the blood vessels. Law's texture features were used for segmenting the blood vessels. Method focuses on the relation between fovea (darkest black region in retina) and exudates to intuit the severity of Diabetic Retinopathy. Shortcoming of the methodology is that neural network classifier for blood vessel demarcation has higher negative prediction value.

Computer aided screening system[6] employs a hierarchical lesion classification methodology where in the microaneurysms and haemorrhages constituting the Red lesions are identified using Gaussian Mixture Model classifier and the disease severity is estimated.

3. Proposed System

Figure 2 depicts the process of Diabetic Retinopathy Screening System. The proposed system consists of three stages namely Image Segmentation, Lesion Classification and DR Severity Grading. Several public databases containing retinal images for DR screening are available. DIARETDB1[7] dataset containing 89 images and MESSIDOR dataset containing 1200 images are most commonly used in DR screening. In the proposed system input images are taken from MESSIDOR[8] dataset.

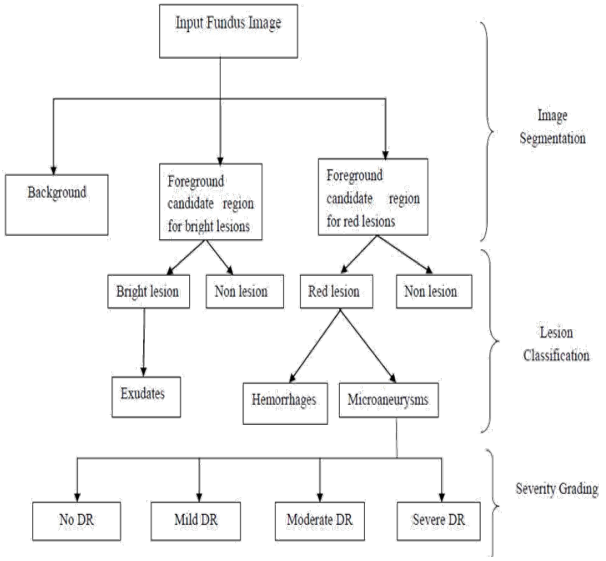

Figure 2. Diabetic Retinopathy screening system.

3.4 Image Segmentation

3.1.1 OD (Optic Disc) Detection

The blood vessels offshoot at the OD, the OD should generally be situated at the junction of one of the giant and darkest regions (blood vessels) and one of the beaming regions (OD) in the image. In a scaled image bright pixels proceed towards one (1) and red pixels proceed towards zero (0), thus the aggregate of independent pixel intensities within a disc shaped mask applied to all the regions of crossing will experience more number of pixels proceeding towards zero close to OD. Thus, the OD would become visible at the crossing region with least pixel intensity within a disc shaped mask and maximum solidity.

OD detection and masking is essential as optic disc can be misinterpreted as bright lesion. Minimum Intensity Maximum Solidity (MinIMaS) algorithm[9] is used for the detection of OD. Threshold value for intensity is set as 0.90 and solidity is calculated as follows:

$$\text{Solidity} = \frac{Area}{Convex\ Area} \quad (1)$$

3.1.2 Vascular Arc Detection

Vascular arc detection and masking is necessary to reduce the false interpretation of arteries of retina as red bruise/lesion. Gradient smoothing of images is achieved by using median filtering. Background image on subtraction from gray image yields Shade Corrected foreground image. Global threshold[10] is applied to the image and the high pixel intensity values are retained which is the vasculature.

3.1.3 Detecting Bright and Red Lesion Candidate

Image is subjected to contrast enhancement, morphologically eroded and then image is reconstructed. This image is subtracted from grey image yielding bright region. Finally vasculature and OD are subtracted from the bright region image and image containing candidate region for bright lesion is obtained.

Red lesion candidate region is obtained by eliminating the vasculature and OD from the shade corrected foreground image.

3.2 Hierarchical Lesion Classification

Lesions are classified as TBL and nonlesion and TRL and nonlesion to reduce the false positives. In this first step of lesion classification GMM classifier is used. In the second step of classification TBL is marked for exudates and TRL is classified as HA and MA based on the feature vectors

3.2.1 Classification Stage 1

Feature vectors6 are extracted for the classification purpose. Each candidate foreground object is then grouped using the 30 structure based features some of which are described in Table 1. The feature vector (x) match to each object in the feature space is calculated. While training the images for lesion grouping, the 30-dimensional feature space, with each dimension depicting a particular feature, is occupied with the objects from the training set of images. The location of each object in the feature space is insistent on by the feature vector (x) and the class labels of the objects corresponding to the training dataset (y) are used to learn the class labels of objects corresponding to the test dataset (y*).

Table 1. Some of the features for classification stage 1

S.no	FEATURES
1	Area : Total pixels in the object
2	Minimum distance from the center of ROD
3	Variance of pixels for the object Igreen
4	Mean of pixels for the object region in Igreen
5	Variance of pixels for the object region in Igreen
6	Variance of pixel intensities for the object region in
	Ired
7	Variance of pixel intensities for the object region in
	Isat
8	Mean pixel intensity for the object region in Ired
9	Variance of pixel intensities for the object region in
	Iinten

3.2.2 Classification Stage 2

In the second stage of classification exudates in the bright lesion image are identified and MA in the red lesion candidate are identified through the features described[11–13] in hemorrhages are identified using mathematical and morphological methods.

3.2.2.1 Exudate identification[14]

From the true bright lesion region obtained from Stage 1, features like aspect ratio, normalized intensity and normalized mean intensity are used to find out the exudates.

3.2.2.2 Microaneurysms Detection

Microaneurysms are detected from TRL region obtained in lesion classification Stage 1. Vector containing linear indices of nonzero elements in the image array are found. Morphological cleaning is carried out and edges are detected by means of canny edge detector. Threshold value of 0.90 - 0.95 is set and structural metrics such as area, perimeter, circularity, compactness and boundary are calculated. The metric results that lie between the threshold values are marked as microaneurysms.

3.2.2.3 Haemorrhage Identification

Haemorrhage is detected through mathematical and morphological operations[15]. Closing operation follows strengthening so that the arteries are suppressed and the

original haemorrhage size is obtained. The number of haemorrhages and the space occupied are found out by means of component labelling technique.

3.3 DR Severity Grading

Based on the number of microaneurysms and haemorrhages count that are detected in the previous stage, the severity of DR is given determined as Grade 0, Grade 1, Grade 2 and Grade 3. Grade 0 specifies the patient does not have DR, Grade 1 represents the patient is having mild DR, Grade 2 indicates that the patient is suffering from moderate DR, Grade 3 shows that patient is having severe diabetic retinopathy. The specifications given in Table 2 specifies disease severity and are taken from the MESSIDOR database.

Table 2. DR severity grading

GRADE	Microaneurysms	Haemorrhages
0	0	0
1	0<MA≤5	0
2	5<MA≤15	0<HA<5
3	MA≥15	HA≥5

Advantages of the system includes the following:

- False positive lesions are minimized.
- Poor quality images are accepted for screening.
- Severity of the disease can be identified.
- Images are not restricted to fixed Field Of View (FOV).

4. Results and Discussion

The performance of three stages of the algorithm are analyzed individually. 100 images from MESSIDOR dataset were used for analysis. Image segmentation which is the first stage, involving detection and masking of OD and blood vasculature is carried out through Minimum Intensity Maximum Solidity (MinIMaS) algorithm achieves 91% accuracy in detecting OD compared to earlier methods such as Haar – based Wavelet Transform (70%), Highest Average Variation (65%). Effectiveness of the second stage of the proposed method, which is significant stage for determining the severity of the disease are discussed as follows:

The standard of measurement used for evaluating the performance of the second and third stages of the detection system are given in terms of True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN) and calculated as follows:

- Sensitivity (SEN) = TP/(TP+FN) (2)
- Specificity (SPEC) = TN/ (TN+FP) (3)

Sensitivity is measured in accordance with False Negatives and True Positives. TP are the actual bright lesions and FN denotes the actual bright lesion that are shown as normal spots. The specificity values are measured in correspondence to True Negatives and False Positives. TN are lesion spots that are missed during lesion detection and FP specifies the nonlesion region marked as lesion spot. Table 3 shows the sensitivity and specificity measures for bright lesion classification. Existing Gaussian Mixture Model (GMM) classifier is compared with that of the proposed Support Vector Machine (SVM).

Table 3. SEN/SPEC for two hierarchical step bright lesion classification

No of	Existing system		Proposed system	
features	SEN	SPEC	SEN	SPEC
5	0.62	0.85	0.67	0.85
10	0.66	0.85	0.76	0.85
15	0.73	0.85	0.81	0.85
20	0.79	0.85	0.81	0.85
25	0.87	0.85	0.84	0.85
30	0.86	0.85	0.89	0.85

Table 4. SEN/SPEC for two hierarchical step red lesion classification

No of features	Existing system		Proposed system	
	SEN	SPEC	SEN	SPEC
5	0.60	0.84	0.61	0.85
10	0.69	0.83	0.64	0.85
15	0.75	0.85	0.73	0.84
20	0.77	0.85	0.79	0.85
25	0.79	0.84	0.79	0.85
30	0.80	0.85	0.82	0.85

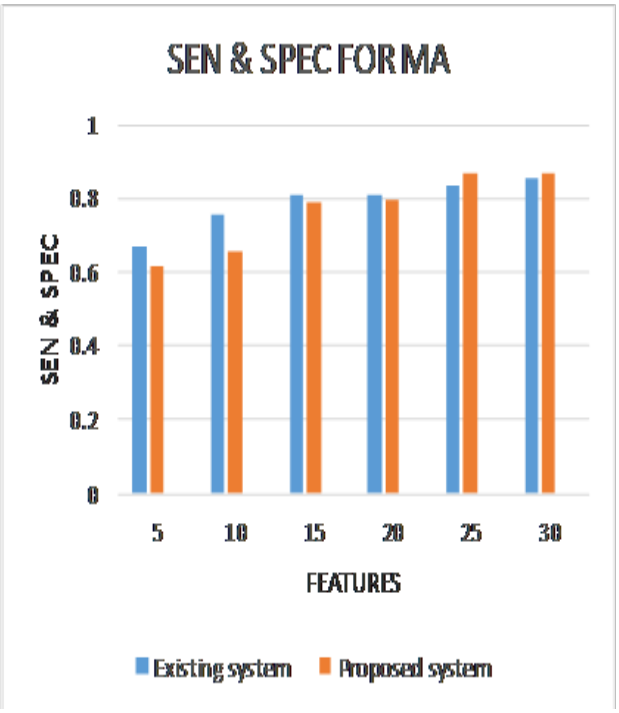

Figure 3. Sensitivity and specificity chart for microaneurysms.

Table 5. SEN/SPEC for two hierarchical step MA detection

No of	Existing system		Proposed system	
features	SEN	SPEC	SEN	SPEC
5	0.67	0.85	0.62	0.85
10	0.76	0.85	0.66	0.85
15	0.81	0.85	0.79	0.85
20	0.81	0.85	0.80	0.85
25	0.84	0.85	0.87	0.85
30	0.86	0.85	0.88	0.85

Table 4 represents the sensitivity and specificity values for red lesion classification as TRL and nonlesion. As for the bright lesion sensitivity and specificity calculation, here also TN, TP, FN, FP are used for SEN and SPEC calculation. TRL are used in this method for predicting the severity of the disease.

Table 5 shows the sensitivity and specificity measurements for microaneurysms detection.

Figure 3 shows that the proposed system achieves greater sensitivity when compared to the existing system.

Figure 4 shows 1. Input retinal image, 2. Vasculature detected, 3. Optic Disc detected, 4. Detected Exudates, 5. Microaneurysms and 6. Haemorrhages.

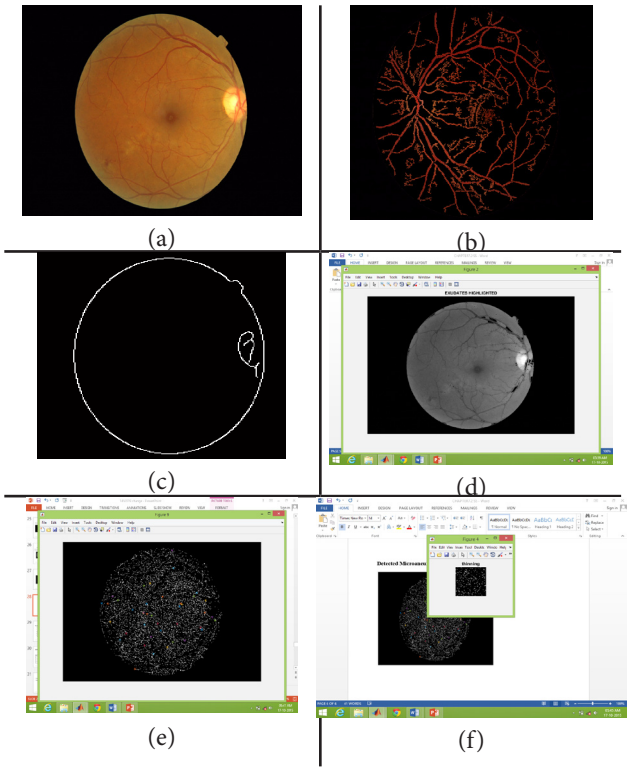

Figure 4. Images from proposed system.

5. Conclusion

Diabetic Retinopathy screening system, developed using 30 features for lesion classification which is expandable across retinal image datasets with different FOV. First stage of the system is crucial as it reduces the false positives, however in some fundus images OD is not completely masked because of extra retinal abnormalities such as myelination. Since bright lesions are not analysed for severity grading this does not pose a problem. Lesion classification in the second stage can deal with unbalanced datasets. DR severity grading is found out by the count of number of haemorrhages and microaneurysms. Grading the severity of the disease with accuracy helps ophthalmologists in better treatment.

Future work can be focussed towards enhancement of the DR lesion grouping performance. Detection of Neovascularization and drusen can also be paid attention in the future work.

6. Acknowledgment

The author thanks all helped to gain knowledge in pursuit of this research work.

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