A Novel Approach on Macular Edema Detection and Classification

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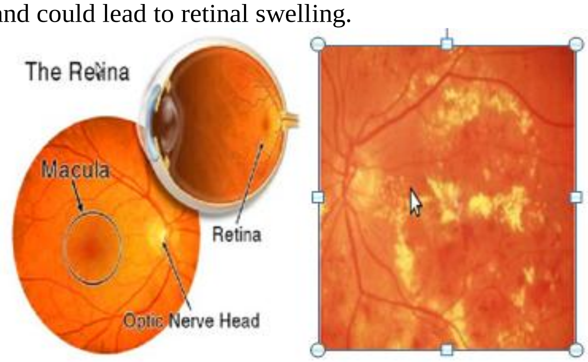
Abstract

Diabetic Retinopathy damages the retina and is caused by complications of diabetes. Diabetic Macular Edema (DME) is caused due to the advanced stage of diabetic retinopathy, which can cause irreversible loss of vision. Exudates are the primary signs of DME. In this paper, a two-stage methodology is developed in order to detect, localize and classify the exudates from the color fundus images is presented. A new Feature Extraction technique, using a Gabor Filter is introduced in order to capture the important features like mean, median, fovea region etc and for enhancing the given retinal image. The selected feature vectors are classified into exudates and non-exudates using a Feed Forward Neural Network Classifier. The analysis of the severe stage of DME is carried out using Morphological Operation. This technique can assist the Ophthalmologists to detect the signs of Diabetic Maculopathy in the early stage, in monitoring the progression of the disease and for better treatment plan. The performance parameters are estimated with a Sensitivity of 95% and Specificity of 89%. The severity classification accuracy is 93% for all severe cases.

Keywords- *Exudates, Gabor Filter, Morphological Operation*

1. Introduction

Diabetic Macular Edema (DME) is caused due to advanced stage of Diabetic Retinopathy. It is a high risk complication which can cause irreversible loss of vision in chronic diabetic patients. Early detection of even minor signs of DME is essential as it might appear without any external symptoms. Once detected during retinal examination, demands immediate treatment ranging from glycolic and blood pressure control, to laser surgery. DME is generally detected directly or indirectly. Indirect method is by detecting the presence of Hard Exudates (HE) in the retina. Hard Exudates are formed due to secretion of plasma from capillaries resulting from the complications of retinal vasculature and could lead to retinal swelling.



(a) (b)

Figure 1 (a) Anatomical structure of retinal image (b) Hard Exudates

Detecting the presence of hard exudates in different areas of retina is now considered as a standard method to asses DME from color fundus images. The severity risk of edema is evaluated on the basis of proximity of HE to the macula, which is defined to be a circular region centred at fovea and with one optic disc (OD) diameter [1]. The risk of DME increases when the HE locations approach the macula, with the risk being the highest when they are within the macula. This is an important factor in DME assessment for further referral of the patients to an expert.

The manual assessment however is not scalable in large-scale scenario, particularly in developing countries either due to the scarcity of skilled manpower or unavailability of high end imaging equipment at the point of care [3]. With the ever increasing diabetic population and the availability of fundus images in digital format there is a need for computer-based retinal screening systems. In such a scenario, we aim to develop a solution for automatic detection and classification of DME from color fundus images.

Progression of diabetic maculopathy is slow and silent, very often without any symptoms in the early stages. If maculopathy is not detected in the early stage then the damage of the macula or visual fields irreversible and can lead to blindness. Therefore, compulsory regular screening of diabetic eye will help to identify the maculopathy at initial stage and reduce the risk of severe vision loss. In ophthalmology, retinal digital imaging provides a permanent, high quality record of the appearance of the retina with application for screening program of the disease.

2. Literature Review

2.1. Automated Detection of Diabetic Retinopathy

In this work, the result of an automated detection of diabetic retinopathy on digital fundus images by Recursive Region Growing Segmentation (RRGS) algorithm where the performance was measured on 10 x 10 patches rather on the whole image. The detected candidate exudates regions are further processed by using a combination of RRGS and adaptive intensity thresholding. Poor quality images affected the separation result of bright and dark lesions using thresholding.

2.2. Evaluation of an Automatic Detection System

In this approach, the reduction in time and effort will be significant where a majority of patients screened for diseases turn out to be normal. The ratio of normal patients to the ones showing disease symptoms can be as high as 9 to 1 DR screening. Several attempts have been reported towards building an automated solution for DR detection. This task is extremely laborious, a large fraction of cases turn out to be normal indicating that much of this time is spent diagnosing completely normal cases. The automated diabetic retinopathy problem is a hard computer vision problem whose goal is to detect features of retinopathy, such as haemorrhage's and exudates, in retinal color fundus images. The advantage of this approach is that it classifies each new image is less performed an evaluation of our optic disc detection mechanism. There is a disadvantage of the equal error rate as 87%.

2.3. Computational Intelligence based Exudate Detection

A method for automatic identification of exudates based on Computational Intelligence technique is introduced. The color retinal images were segmented using fuzzy c-means clustering. Feature vector were extracted and classified using multilayer neural network classifier, identified the exudates using Global and Local thresholding. The input images were pre-processed to eliminate photographic non-uniformities and the contrast of the exudates was then enhanced. The lesion based sensitivity of this technique was reported between 61% and 100% based on 14 images. A drawback of this method was that other bright lesions (such as cotton wool spots) could be identified mistakenly.

2.4. Efficient Approach for Detection of Exudates

An Efficient Approach for detection of exudates in Diabetic Retinopathy images using Clustering techniques is used here. Automatic recognition of DR lesions like exudates, in digital fundus images can contribute to the diagnosis and screening of the disease. In this approach, an automatic and efficient method to detect the exudates is presented. To classify these segmented regions into exudates and non-exudates, a set of features based on color and texture are extracted. Classification is done using Support Vector Machine classifier. This method appears promising as it can detect the very small exudates. The advantages are reduced computational time, flexibility to represent complex functions. The disadvantage is complexity by minimizing an upper bound on the generalization error.

2.5. Automatic Assessment of Macular Edema

A method for DME detection via a supervised learning approach using the normal fundus images. A feature extraction technique is introduced to capture the global characteristics of the fundus images and discriminate the normal from DME images. Disease severity is assessed using a rotational asymmetry metric by examining the symmetry of macula region. The performance of the proposed methodology and features are evaluated against several publically available datasets. The detection performance has a sensitivity of 100% and specificity in between 74% and 90%. Cases needing immediate attention are detected with a sensitivity of 100% and specificity of 97%. The severity classification accuracy is 81% for the moderate cases. The disadvantage of this method is that the classification accuracy sometimes falls as the value of the feature space is increased to 75%. This implies that of the normal region of interest (ROI) is sensitive to intensity variations but does not affect the classification accuracy of severe cases.

3. Automatic Diagnosis of DME

This work introduces a system uses the combination of image processing and machine learning techniques for the detection of exudates, a sign of DME in retinal images. The exudates are identified from gray level images. The Gabor Filter is applied to the gray scale images for extracting the relevant features from the color fundus image. The features like mean, median, sum of pixels in the fovea region etc are extracted and the candidate regions are given as input to a Feed Forward Neural Network classifier. The performance parameters such as sensitivity, specificity and accuracy are estimated.

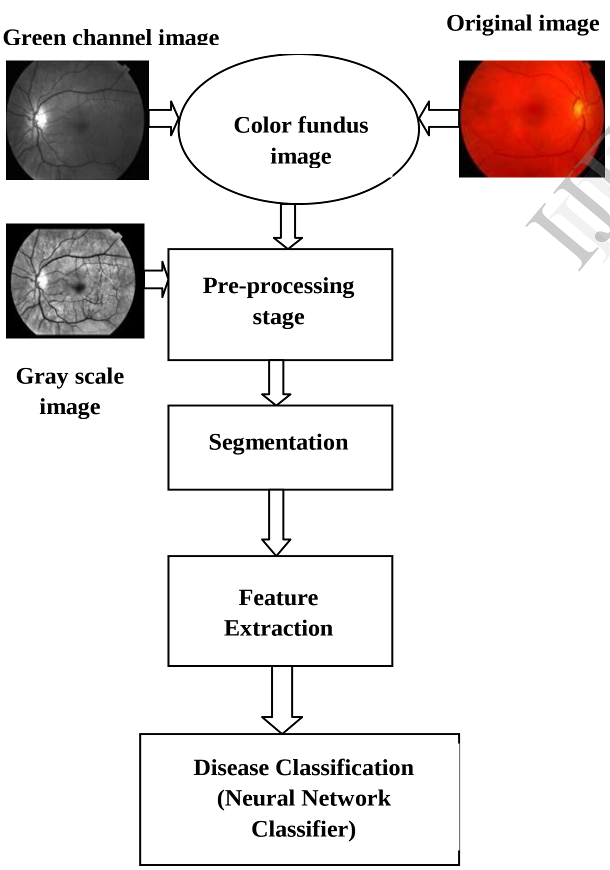


Figure 2 Block Diagram of Automatic Diagnosis of DME from color fundus image

3.1. Pre-processing Stage

The retinal images are collected from Messidor, Diaretb0 databases which are freely available. Images are also collected from Aravind Eye Hospital. Dimensions of images are 2124x2056 pixels. The input image can be a color or a gray level image which is applied to the pre-processing stage. This particular stage corrects the problem of illumination variation that occurred when the pictures are taken.

Other problems corrected by this process include the enhancement of the contrast between the exudates and vein network and the background to aid in segmentation and detection of the abnormalities [4]. The processes involved are Color space conversion, Zero padding of image edges, Morphological operation and Histogram equalization. The output of this stage is passed into the segmentation stage.

3.1.1. RGB to Binary Word Image Conversion

RGB to Binary word image conversion can be achieved in order to obtain the image in terms of black (0's) and white (1's) components. This conversion can be done in the system by using the keyword "Ibw" in Mat lab software. The result of color space conversion is fed to the edge Zero padding stage for further processing.

3.1.2. Edge Zero Padding Stage

Image is padded with zeros so as to remove unwanted noises. Padding is used for intensity enhancement and segmentation.

3.1.3. Histogram Equalization

This method of image processing is contrast adjustment using the image's histogram. It can improve the global contrast of the image. It also helps the area of lower contrast to gain a higher contrast and bringing out more detail.

3.1.4. Morphological Operation

The special applications are seen in the field of machine vision and automatic object detection. The operators used for morphological operation are dialation, erosion, opening, closing and skeletonization etc. The opening and closing are implemented in Mat lab by the use of imopen (image name) and imclose (image name) respectively.

The erosion shrinks or thins the objects in a binary image by the use of structuring element. On the other hand dialation is the process that thickens objects in a binary image. The extent of thickening is controlled by the structuring element (SE) which is represented by a matrix 0's and 1's. The opening deals with erosion operation followed by dialation operation whereas closing deals with dialation operation followed by erosion operation. During the morphological processing, dilation is performed on the green channel

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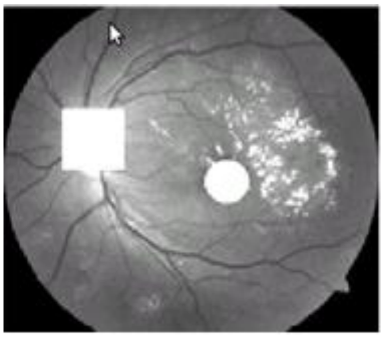

Figure 3 Masked Optic Disc

extracted image across two disc shaped structuring elements. The results are subtracted to get the boundary of hard exudates. Opening is to remove small bright details. Thus possible candidates of HE are obtained.

The Hard Exudates (HE) and Optic Disc (OD) are of same brightness, color and contrast. Hence OD is sometimes misclassified as HE. Therefore, OD is detected and eliminates from possible candidates. To detect OD we can use circular Hough transform. Thus the OD is detected automatically and masked (see Figure 3).

3.2. Segmentation

Segmentation is an important pre-processed step. The local contrast enhancement was performed to distribute the values of the pixels around the local mean to facilitate later segmentation. Hard segmentation methods take crisp decisions about regions [5]. However, the regions in an image are not always crisply defined.

Figure 4 Segmented image

The main objective of segmentation is to group the image into regions with same property or characteristics. Segmentation can also be defined as a method to divide an image into its constituent regions or objects. It takes a major role in image analysis system by facilitating the description of anatomical structures and other regions of interest. The output of segmentation result is passed onto the next stage, that is, feature extraction.

3.3. Feature Extraction

In order to classify the candidate exudates regions as exudates and non-exudate region, we extracted a set of features from each region and used them as inputs to the Neural Network classifier. To select an adequate set of features, we focussed on those characteristics that ophthalmologists use to visually distinguish exudates from the retinal background and other retinal lesions or structures. The features such as mean, median, sum of pixels in the fovea region, fovea area etc are extracted for this work.

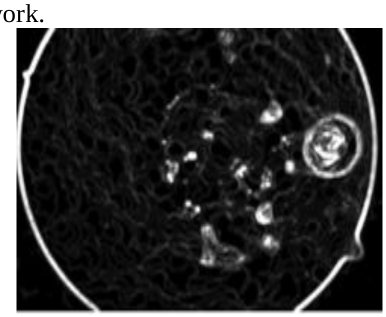

Figure 5 Enhanced bright regions using Gabor filter bank

We use a Gabor filter bank for detection of all possible bright regions. Gabor filters are famous due to their fine frequency tuning and orientation selectiveness. They are appropriate for texture representation and discrimination. Gabor filter is having wide range of shapes depending upon values of its parameters in detecting the bright regions.
The Gabor filter bank equation is given as,

$$\mathbf{Gfb} = \frac{1}{\sqrt{\pi r\sigma}} e^{-\frac{1}{2}\left[\left(\frac{d1}{\sigma}\right)^2 + \left(\frac{d2}{\sigma}\right)^2\right]} \mathbf{(d1(\cos\Omega + i\sin\Omega))}$$

where,
σ is the standard deviation of Gaussian,
Ω is the spatial frequency,
$d1 = x\cos\theta + y\sin\theta$ and $d2 = x\sin\theta + y\cos\theta$
Θ is the orientation of the filter.

The Gabor filter makes use of Gabor functions which are sinusoidally modulated Gaussian functions that provide optimal localization in both the frequency and space domains; a significant amount of research has been conducted on the use of Gabor functions or filters for segmentation, analysis and discrimination of various texture and curvilinear structures.

3.4. Classification using Neural Network Classifier

This paper investigates the application of Feed Forward Neural Network for detection of exudates in retinal images. Neural network is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. We define a neural network with one input layer, hidden layer and one output layer.

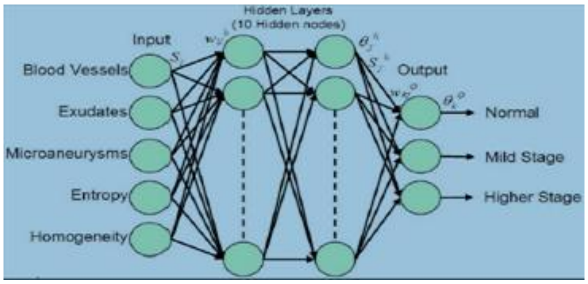

Figure 6 four layer feed forward neural network

The feed-forward neural network architecture is commonly used for supervised learning. Feed-forward neural networks contain a set of layered nodes in adjacent layers. Feed-forward networks are often trained using a back propagation learning scheme. Advantages of neural networks, however, include their high tolerance to noisy data as their ability to classify patterns on which they have not been trained.

4. Results and Discussion

In this work, we have investigated and proposed a new method to automatically detect and classify the color fundus image with the help of a Gabor filter and Feed-forward neural network classifier. The implementation results are as follows:

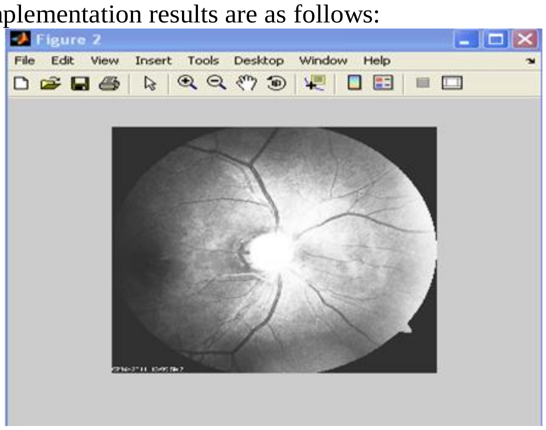

Figure 7 Enhanced image of a normal color fundus image

The figure 7 shows the contrast adjusted image. The local contrast enhancement is performed to distribute the values of the pixels around the local mean to facilitate later segmentation. The figure 8 infers to the morphological opening-closing operation. Thus, the possible candidates of HE are obtained.

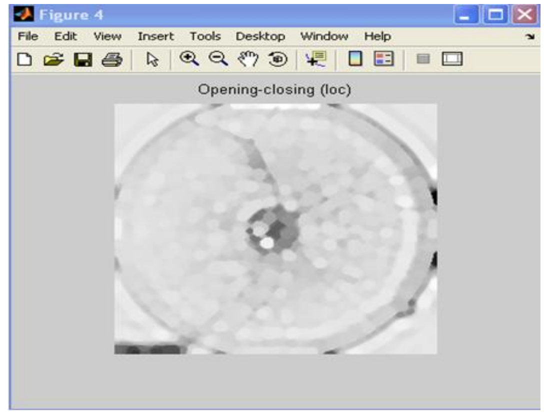

Figure 8 Image obtained after morphological opening-closing

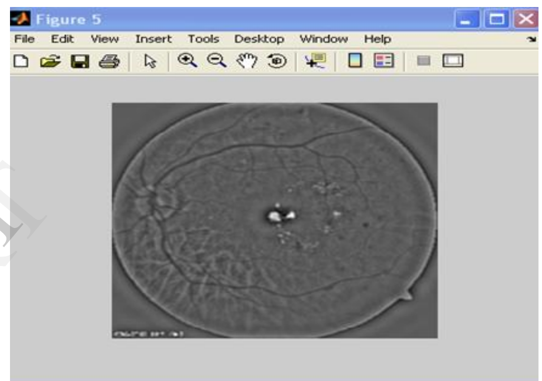

Figure 9 Pre-processed abnormal fundus image

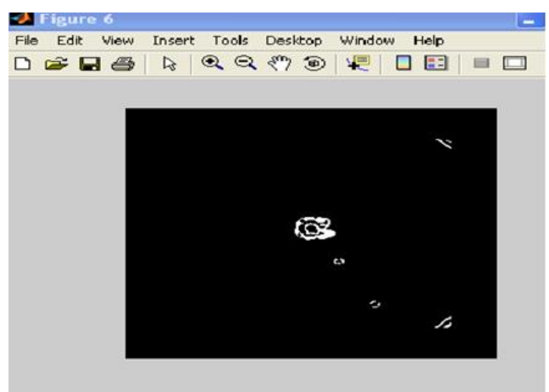

Figure 10 Exudates are spotted in a disease person's fundus image

The Figure 8, 9 and 10 shows the fundus image of an abnormal or diseased patient. Hard exudates are formed due to secretion of plasma from capillaries resulting from retinal swelling. Here the exudates can be easily spotted out. Then the disease classification stage utilizes a Feed-forward neural network classifier for separating normal from diseased images.

Table 1 Performance Evaluation

Classifier	Image type	No. of patients	Detected as Abnormal	Detected as Normal	X = Sensitivity Y = Specificity
Feed forward Neural network	Abnormal	40	38	2	X = 95%
	Normal	27	3	24	Y = 89%
					Accuracy =93%

Thus, these results establish the effectiveness of the proposed solution with improved accuracy. It also states a minimum standard of 95% sensitivity, 89% specificity and 93% accuracy for a total of 67 retinal images consisting of normal and abnormal images.

6. Conclusion

The Diabetic Macular Edema (DME) is an advanced symptom of diabetic retinopathy. DME detection is carried out via a supervised learning approach using the normal fundus images. The feature extraction is done using Gabor filter which increases the efficiency of the system than while using the motion pattern approach. The global characteristics of the fundus image are captured and thus, discriminated the normal from DME images. The disease severity is assessed using a Feed-forward Neural network classifier.

The proposed methodology enhances the existing DR screening infrastructure by helping automated detection and classification of DME. This method have successfully analysed the textural features like mean, median etc of the image. The performance parameters are estimated as follows: Sensitivity as 95%, Specificity as 89% and accuracy as 93%.

7. Future Work

Although the results obtained from this work are efficient enough, there areas that can be improved to raise the overall accuracy of the system. The Neural networks can get stuck in local saddle points and therefore, they are susceptible to many training problems including overfitting and convergence. It is believed that SVM classifiers are a more practical solution to this application because they have sensitivity and specificity control and do not suffer from overfitting problems and hence generalize better.

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