Detection and Classification of Age Related Macular Degeneration in Retinal Images using Support Vector Machine Classifier

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Abstract— Nowadays retinal diseases are quite common in elderly people. In some cases retinal diseases can even leads to permanent blindness, one such retinal disease is Macular degeneration. Macula, it is central part of retina responsible for the sharp central vision needed for detailed activities that requires central vision such as reading, writing, driving. But progressive destruction of delicate cells of macula leads to a condition called Age related macular degeneration (ARMD or AMD). Fatty deposits called as drusen will accumulate in macula region which progressively destructs the macula and in the worst case it even leads to permanent blindness. In this paper an algorithm for semi-automated detection of AMD using image processing techniques using fundus images have been proposed. The proposed method includes pre-processing, segmentation and feature extraction techniques. Feature extraction includes Gray Level Co-occurrence matrix (GLCM), which is used to extract the features which are required for the classification process. The classification results are evaluated with the use of accuracy, sensitivity and specificity with the help of Support Vector Machine (SVM) classifier. Proposed method obtains accuracy 94.12%, sensitivity 91.66% and specificity 100%.

Key words: Fundus Image, Drusen, SVM, GLCM, AMD

I. INTRODUCTION

Age related macular degeneration is the degeneration of the macular area. Sometimes the delicate cells of the macula become inactive and stop sensing. Currently, there is no permanent cure for AMD, however early detection and subsequent treatment may prevent the severe vision loss or slow the progression of the disease. AMD can be classified into two types dry and wet AMDs. Early symptoms of AMD are formation of drusen or yellow pigmentation. Types of AMD are explained briefly as follows:

- Dry macular degeneration is an early stage of the disease caused by the lack of functioning of visual cells in the macula region that deteriorates slowly. Initial symptoms of dry AMD are the presence of yellow fatty deposits, called drusen, on the retina. It generally affects both the eyes and patients can see a blurred vision. There is no treatment for dry type. Most of the people with macular degeneration are affected by the "dry" type.
- Wet Macular Degeneration affects the retina when abnormal blood vessels start growing in macula where they are not supposed to be. Due to the abnormal blood vessels it leads to filling of fluid under the retina. That also leads to bleeding causing loss of vision. It progresses rapidly and may respond to laser treatment only in the early stages. Fig. 1 shows the normal vision and vision of a person with Age Related Macular degeneration.

Fig.1 Effect of AMD in human vision: (a) normal vision (b) vision of person with AMD.

In order to carry out characterization and classification of normal and abnormal retinal images which detects as AMD feature extraction technique namely GLCM, mainly Haralick's textural features [1] are used. GLCM calculates the probability of a pixel with the gray-level value *i* occurring in a specific spatial relationship to pixel with the value j [2]. Using Haralick's statistical approach, mainly four distinguished features were extracted which are useful in classifying the retinal images as AMD or normal image.

Agurto et al. [3] have proposed AM–FM based AMD detection using retinal fundus images. Their approach decomposed the green channel image into different representations using AM–FM method on 140*140 pixels region of interest (ROI) which reflects the intensity, geometry and texture of the different lesions present in the image. Further, features such as statistical moments and histogram percentiles are computed. Finally, partial least square method is used to classify the features as DR and AMD. They have achieved AUC of 0.84 and 0.77 respectively. M. Ponni Bala et al. [4] have proposed Computerized Retinal Image Analysis to Detect and Quantify Exudates Associated with Diabetic Retinopathy. They have proposed a new feature based automated technique for classification and detection of exudates in color fundus image. In their work, exudates are separated from the fundus image by thresholding and removal of optic disk using morphological operation and connected component analysis. Finally, an automated Fuzzy Inference System (FIS) has been used for classifying the retinal images as exudates and its severity and non-exudates. The sensitivity, specificity and accuracy are reported in their work as 91.11%, 100 % and 93.84% for Fuzzy Inference System Classification.

A Rama Prasath and M.M Ramya [5] have proposed an algorithm for drusen detection based on GLCM based textural features. Localization of the optic disc (OD) and blood vessels were done using morphological operators. Their algorithm detects macula region based on the location of the vessel arcades and the OD. The performance of their system was evaluated by comparing the drusen detected output images with hand-labelled ground-truth images graded by the experts. The receiver operating characteristic curve of the proposed system provides over 98.05% segmentation accuracy.

S. Karthikeyan and Dr. N. Rengarajan [6] have proposed a system for analysis of gray levels for retinal image classification. Fundus images from glaucoma patients were taken and processed using histogram equalization. First order features from histogram and twenty two second order features from GLCM are extracted. Extracted features were given to back propagation network to classify images as normal and abnormal. Their proposed computer aided diagnostic system achieved 92% sensitivity, 94% specificity and an accuracy of 93%.

II. METHODOLOGY

The objective of this work is to classify the retinal image consisting of drusen or normal retinal images. Flow chart of the proposed method is shown in Fig. 2. The retinal image used for this work is first subjected to the preprocessing steps such as green channel extraction, histogram equalization and contrast enhancement in order to remove noise and to obtain better contrast of the image. Preprocessed images are then subjected to segmentation and features like texture properties are extracted from segmented images.

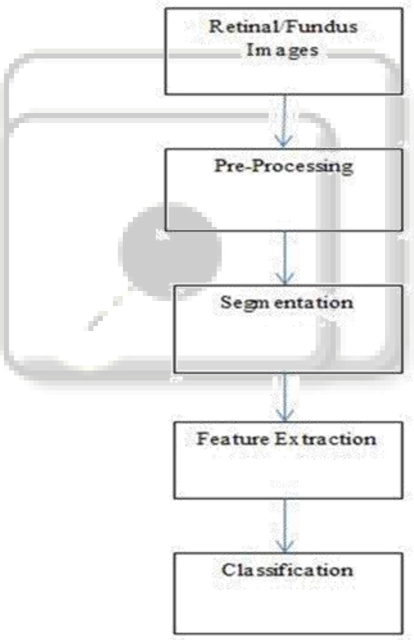

Fig. 2: Flow Chart of the proposed work

A. *Image Acquisition*

Two publicly available databases such as ARIA (http://www.eyecharity.com/aria_online) and STARE (http://www.ces.clemson.edu/ahoover/stare) databases are used to test the performance of the proposed AMD detection system.

Retinal images from ARIA databases were acquired using Carl Zeiss Meditec fundus camera with 50 degree field of view and a resolution of 768*576 pixels. STARE database images were acquired using TOPCON camera with 35 degree field of view with a resolution of 700*605.

B. *Pre-Processing*

The retinal images in the dataset are often noisy and poorly illuminated because of unknown noise and camera settings. Also there is a wide variation of color of retina from patient to patient. Thus the images are subjected to various preprocessing steps, which include green channel extraction and contrast enhancement. Drusen appear bright in the green channel compared to red and blue channels in RGB image. Hence green channel is used for further processing by neglecting other two components. Top Hat transform and contrast enhancements are used to increase the contrast between the drusen and the image background. Pre-Processed images are shown in the below Fig.3.

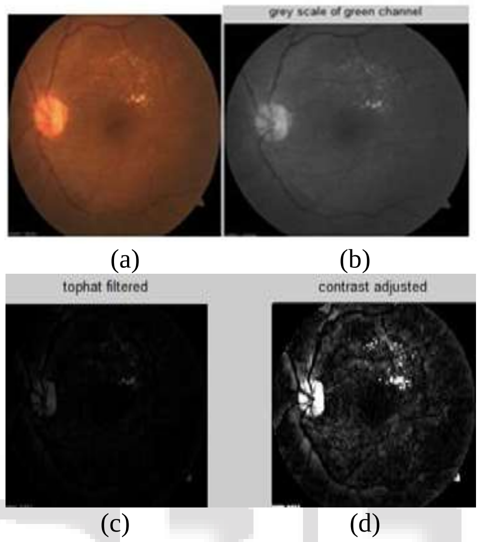

Fig. 3: Pre-Processing Stages (a) Original Image (b) Green Channel Image (c) Top hat filtered Image (d) Contrast adjusted

C. *Segmentation*

Segmentation subdivides an image into its constituent regions or objects that have similar features according to a set of predefined criteria. Thresholding is a fundamental tool for segmentation of grey level images when objects and background pixels can be distinguished by their grey level values. Here optimal thresholding is used to segment drusen area from other background image. Algorithm for obtaining optimal threshold from image histogram:

To obtain an optimal threshold, histogram derived from the source image I is scanned. The initial threshold Tk for step k=1 is taken as the mean of t2 and t1 resulting in subset of histograms. Formulation for the calculation of optimal threshold is given by the following pseudo code.

1) Initial estimate of Tk is calculated at step k as Mean Intensity
$$Tk= \frac{sum\ of\ all\ brightness\ value\ observations}{number\ of\ observations}$$
2) At step k, apply the threshold. This will produce two groups of pixels: Go consisting of all pixels belonging to object region and Gb consisting of all pixels belonging to background region.
3) Compute the average intensity values and for the pixels in Go and Gb respectively.
4) Update the threshold as follows:
$$Tk= (\mu_o + \mu_b)/2$$

5) Repeat steps 2 through 4 differences in T in successive iterations are smaller than a predefined value.

Optimal threshold thus calculated results in maximization of gray level variance between object and background.

Fig.4 shows the result of thresholding on one of the test image.

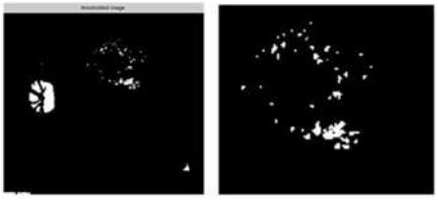

Fig. 4: (a) Thresholded Image (b) ROI extracted with drusens.

D. Feature Extraction

Feature extraction is a method of capturing visual content of an image by representing a raw image in its reduced form to facilitate decision making process namely classification. In this paper GLCM features are extracted from the segmented Region of Interest (ROI) i.e. macular area. Based on texture analysis of the image, using statistical approaches the textural features were extracted.

1) Gray level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix is a matrix where the number of rows and columns is equal to the number of quantized gray levels. The second order statistical probability values for changes between gray level i and j at a particular displacement distance (d) and (θ). The texture-content information is specified by the relative frequency p (i, j), represents the number of occurrence of gray levels i and j within, at a certain (d, θ) pair.

The probability measure is defined as

$$\text{Pro}(x) = \{p(i,j)|(d,\theta)\} \qquad (1.1)$$

$$P(i,j) = \frac{p(i,j)}{\sum_{i=0}^{Ng-1}\sum_{i=0}^{Ng-1} p(i,j)} \qquad (1.2)$$

Haralick extracted 14 textural features using second order statistics by proposing 2 steps for feature extraction

– Computing the Occurrence Matrix
– Calculating texture feature based on the GLCM using statistical approach.

Four distinguished features were used to quantitatively evaluate the textural characteristics of the segmented drusen region.

E. Energy:

Angular second moment also known as energy, is a measure of homogeneity of an image. It ranges from 0 to 1. For constant image, energy value is 1.

$$\text{Energy} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)^2 \qquad (1.3)$$

F. Autocorrelation

Autocorrelation is a measure of the linear dependency of gray levels on those of neighboring pixels or specified points which indicates local gray-level dependency on the texture image.

$$\text{Corr} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_x)(j-\mu_y)p(i,j)}{\sigma_x\sigma_y} \qquad (1.4)$$

G. Cluster Prominence

It is a measure of asymmetry.

$$\text{Cprom} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(i + j - \mu_x - \mu_y\right)^4 p(i,j) \qquad (1.5)$$

H. Inverse Difference Moment

IDM measures the local homogeneity of an image. The result is a Low IDM value for inhomogeneous images and a relatively higher value for homogeneous images.

$$\text{IDM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{((p(i,j))2}{1+(i-j)^2} \qquad (1.6)$$

I. Classification

Features which are obtained from GLCM are applied directly to classifier namely Support Vector Machine where two classes namely normal and abnormal are obtained. Support Vector Machine (SVM) constructs a hyperplane or set of hyperplanes in high or infinite dimensional space which can be used for classification, regression or other tasks. The data that lie on the hyperplane margins are called support vectors. The SVM algorithm classifies the positive and negative examples by training a classifier that uses a kernel function to map the input samples onto a high-dimensional feature space [7, 8] that best differentiates the two classes with a maximal margin and a minimal error.

III. RESULTS

In this paper, statistical textural features are obtained from the ROI i.e. around macula where drusens are present by using feature extraction technique namely GLCM. Obtained feature vectors are then given to SVM classifier to classify the images as normal or abnormal retinal images to detect AMD condition.

A. Experimental Results

The algorithm is tested with 20 retinal images of AMD patients from STARE and ARIA databases. After feature extraction process we obtain average values for normal and abnormal AMD fundus images which are given in Table 1.

Features	Normal Image	Abnormal Image
Energy	1.0002	0.8842
Autocorrelation	1	1.1270
Cluster Prominence	0	0.5297
Inverse difference moment	1.0001	0.9960

Table 1: Average Values Obtained For Both Normal And Abnormal Images

According to the table given we can see that for normal healthy retinal images features like energy, autocorrelation, cluster prominence and inverse difference moment are either almost purely 0 or 1 but for abnormal AMD images, values vary between 0 and 1 in accordance with the severity of the disease.

IV. CONCLUSION

In this paper a novel decision support system has been developed to semi-automatically detect drusen from the retinal images. The proposed algorithm involves pre-processing which is responsible for non-uniform illumination correction and contrast enhancement. Histogram based thresholding is done to segment the drusen region. This study presents a method to quantitatively measure drusen texture features based on GLCM values. Extracted features were given to SVM classifier for classifying as normal or abnormal AMD images. Proposed method obtains accuracy 94.12%, sensitivity 91.66% and specificity 100%.

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