DETECTION OF DIABETIC RETINOPATHY USING LOCAL BINARY PATTERN

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Abstract - *Diabetic retinopathy is a chronic progressive eye disease associated to a group of eye problems as a complication of diabetes. This disease may cause severe vision loss or even blindness. Specialists analyze fundus images in order to diagnostic it and to give specific treatments. Fundus images are photographs taken of the retina using a retinal camera, this is a non-invasive medical procedure that provides a way to analyze the retina in patients with diabetes. The correct classification of these images depends on the ability and experience of specialists, and also the quality of the images. In this paper we present a method for diabetic retinopathy detection using MATLAB. This method is divided into three stages: first stage is pre-processing which involves disk segmentation and vessel segmentation. In next stage which is feature extraction various features like variance, mean, skew, standard deviation of texture are calculated using LBP and watershed algorithms. Finally the classification is done using the SVM by creating a hyperplane and comparing the features with dataset.*

Key Words: Local Binary Pattern (LBP), Support Vector Machines (SVM), Image Analysis, Fundus.

1. INTRODUCTION

Diabetic Retinopathy is the term that is used to describe the retinal damage causing the vision loss. Some people are born with it, whilst others acquire the disease in later life. The body can't store the sugar from food, and it courses through the bloodstream. This sugar reacts with the walls of the blood vessels as it does so, causing them to break down over time. Diabetic Retinopathy will be harmful to the retina. As light beams come into the eye, through the viewpoint, it arrives on the retina to be transform into electrical signs to be sent to the mind. Courses and veins take oxygen and supplements to your retina and diabetes harms and devastate the veins.

The WHO assesses that in 2010 there were 285 million individuals outwardly hindered nearby the globe. Despite the way that the quantity of visual deficiency cases has been essentially decreased as of late, the situation is assessed that 80% of the instances of optical disability are avoidable or curable. DR and age related muscular degeneration is these days two of the greatest continuous reasons of visual deficiency and apparition misfortune. Furthermore, these maladies will encounter a high development later on because of diabetes occurrence increment and maturing populace in the present society.

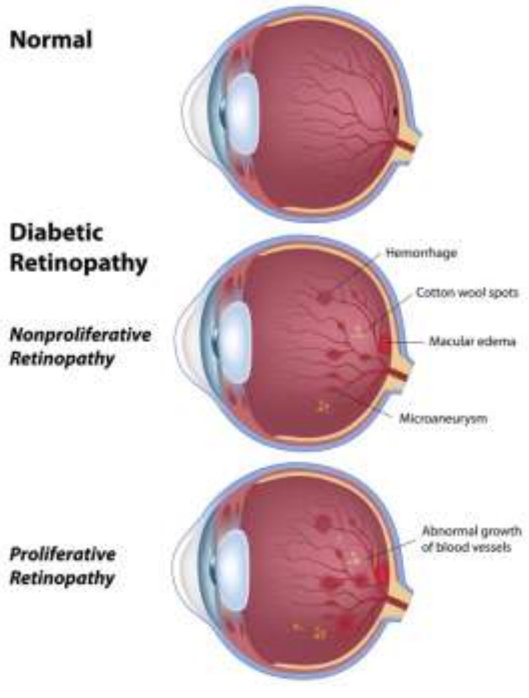

Fig -1 : Normal and Diabetic retinopathy eyes

As this is a rapidly growing problem a proper and definitive solution is needed. In this paper the proposed work will identify the diabetic retinopathy with 98% accuracy using different filtration processes and various algorithms.

2. LITERATURE SURVEY

According to T. Walter, et al. [1] the presence of exudates within the macular region is a main hallmark of diabetic macular edema and allows its detection with a high sensitivity. Hence, detection of exudates is an important diagnostic task, in which computer assistance may play a major role. Exudates are found using their high grey level variation, and their contours are determined by means of morphological reconstruction techniques. The detection of the optic disc is indispensable for this approach. We detect the optic disc by means of morphological filtering techniques and the watershed transformation.

Soares et al. [2] used a Gaussian mixture model Bayesian classifier. Multiscale analysis was performed on the image by using the Gabor wavelet transform. The gray-level of the inverted green channel and the maximum Gabor transform response over angles at four different scales were considered as pixel features. Finally, a support vector machine (SVM) for pixel classification as vessel or nonvessel. They used two orthogonal line detectors along with the gray-level of the target pixel to construct the feature vector.

Keith A. Goatman et al. [3] described a method for automatically deducting new vessels on the optic disc using retinal photography. Aliaa Abdel-Haleim et al. presented a method to automatically detect the position of the OD in digital retinal fundus images. The method starts by normalizing luminosity and contrast throughout the image using illumination.

M. Heikkil et al. [4], a method based on multi-scale Gabor analysis of retinal image was proposed. A feature vector consist of five features was used for vessel segmentation. At each pixel the grey level of the inverted green channel and the response of Gabor transform for four different scales are used as features. At each scale the maximum response of Gabor wavelet over different orientations spanning from 0^o to 179^o at step of 10^o is calculated. Image pixels in this method are classified using Bayesian classifier.

Ricci et al. [5] use only three features for pixel classification: the grey level of the inverted green channel image and response of two line detectors to the neighborhood of the pixel, one perpendicular to another. The basic line detector has length 15 pixels which rotate at 12 different orientations between 0 to 360 degrees. The response of line operator at each pixel along a specific angle is obtained by averaging the grey level of pixels along the line operator. Then the largest response is one of two line features. The average grey level of line with length equal to three pixels orthogonal to the basic line detector is used as another line feature.

3. PROPOSED SYSTEM

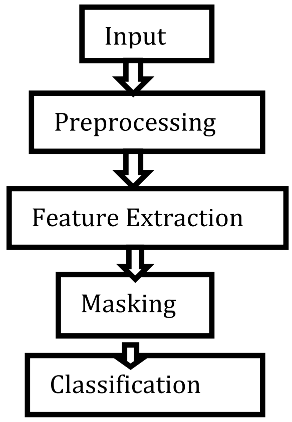

Fig-2 : *Block Diagram*

3.1 Preprocessing:

We use images from different sources, the size of image varies. Hence we need to rescale the images using length of horizontal diameter of fundus as reference.

Here Bicubic interpolation is used for resizing of image. The output pixel is weighted average of pixels in nearest 4*4 neighbourhood. After rescaling, to remove noise we use Median filter using 3*3 neighbourhood.

$$P(x,y) = \sum_{i=0}^{3}\sum_{j=0}^{3} a_{ij}\, x^i y^j$$

4. FEATURE EXTRACTION:

The feature extraction consists of different stages. First we use Water shed algorithm to separate foreground and background of the image. Watershed algorithm which is a mathematics morphological method for image segmentation based on region processing, has many advantages. The result of watershed algorithm is global segmentation, border closure and high accuracy. It can achieve one-pixel wide, connected, closed and exact location of outline.

Then we perform the RGB separation for the processed images. Features are the information extracted from images in terms of numerical values that are difficult to understand and correlate by human. Here we use LBP and VAR operators to characterize the texture of retina background. While calculating LBP and VAR we didn't consider the optic disc and blood vessels.

4.1 LBP Calculation:

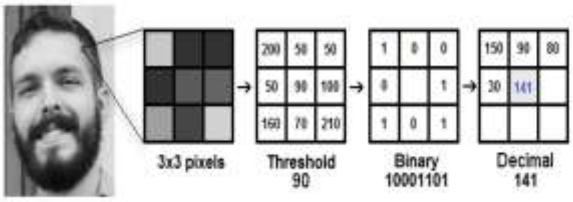

Fig-3 : LBP calculation

A variance image is an image of the variances, that is the squares of the standard deviations, in the values of the input or output images.

$$VAR_{P,R} = \frac{1}{P}\sum_{P=0}^{P-1}(g_p - \mu)^2$$

$$where\ \mu = \frac{1}{P}\sum_{P=0}^{P-1} g_p$$

After this external masking is done, then we will get different features from r, g, b images.

After this we need to find different statistical values of the images like mean, standard deviation, median, entropy, skewness and kurtosis.

4.2 Mean:

It is the average of a set of numbers. To find the mean of a data set, add up all of the numbers in the set, and then divide that total by the number of numbers in the set.

$$\text{mean} = \frac{\text{sum of pixel values}}{\text{total number of pixels}}$$

4.3 Standard Deviation: It is a measure of the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the values are spread out over a wider range.

Here μ = mean value of image

N – Number of pixels

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$$

4.4 Median:

It is the value separating the higher half from the lower half of a data sample, a population or a probability distribution.

4.5 Entropy:

It is defined as corresponding states of intensity level which individual pixels can adapt. It is used in the quantitative analysis and evaluation image details.

$$entropy = \sum_{i=0}^{n-1} p_i \log p_i$$

n = Number of gray levels

P_i = probability of pixel having gray level 'i'

4.6 Skewness:

It is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point.

For univariate data $Y_1, Y_2, ..., Y_N$, the formula for skewness is:

$$\textbf{skewness} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3/N}{s^3}$$

4.7 Kurtosis:

It is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. That is, data sets with high kurtosis tend to have heavy tails, or outliers.

For univariate data $Y_1, Y_2, ..., Y_N$, the formula for kurtosis is:

$$\textbf{kurtosis} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4/N}{s^4}$$

5. CLASSIFICATION

After the feature extraction is done we use support vector machine (SVM) for classification of these into DR and Non-DR.

Support-vector networks are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. According to the SVM algorithm we find the points closest to the line from both the classes. These points are called support vectors. Now, we compute the distance between the line and the support vectors. This distance is called the margin. The hyperplane for which the margin is maximum is the optimal hyperplane.

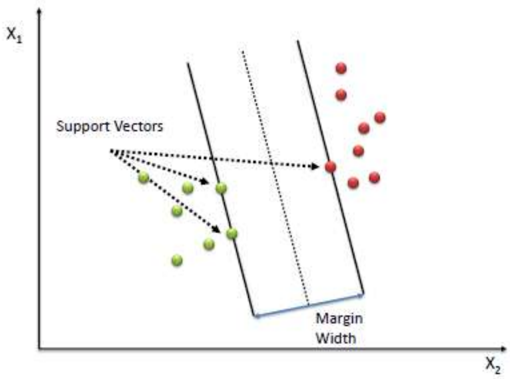

Fig-4 : SVM Classification

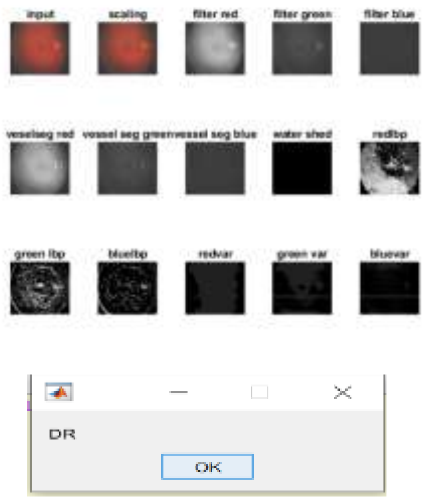

Fig-4 : Sample results

SVM classifier is evaluated by using several parameters such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) are calculated. The parameters are calculated by comparing the classifier outcome with the number of normal and abnormal images from the database.

True-Positive Rate = TP / TP + FN

False-Positive Rate = FP / FP + TN

True-Negative Rate = TN / TN + FP

False-Negative Rate = FN / FN + TP

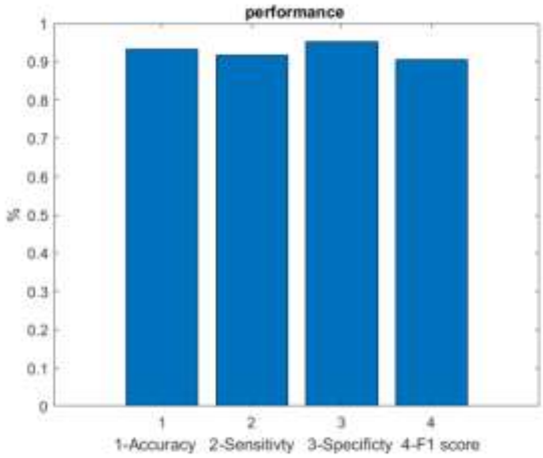

Fig-5 : Performance Values

6. CONCLUSION

In this paper, a new method is proposed for diagnosis of DR. It is based on analyzing texture features and differentiating the fundus images of the healthy patients to diabetic retinopathy patients. The proposed method is capable of discriminating the classes based on analysing the texture of the retina background, avoiding previous segmentation of retinal lesions that might be time consuming and potential inaccurate, thus avoiding the segmentation is beneficial. The obtained results demonstrate that using LBP as texture descriptor for fundus images provides useful features for retinal disease screening. Support vector machine (SVM) can be used to recognize different features on a fundus image of diabetic retinopathy. The MATLAB system can screen fundus with retinopathy with better accuracy using a set of database images.

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