Early Detection of Diabetic Retinopathy in Fundus Images Using GLCM and SVM

S Deva Kumar, Gnaneswara Rao Nitta

ABSTRACT--- ***Diabetes enhances the risk of destruction of blood vessels that pumps blood vessels that pumps blood to the retina an aliment known as Diabetic Retinopathy (DR). In diabetic retinopathy appearing of Microaneurysms is the first clinical sign. Hence, identification of Microaneurysms becomes a major problem solving task, in which fundus images plays a very important role. If this is detected in early stage, it is very much useful to the ophthalmologist to treat the patients in avoiding the blindness of the patients by their treatment. In this paper, we are proposing an automatic method for detection of Microaneurysms from Diabetic Retinopathy fundus photographs. For detecting simple and efficient methods are used. The methods are Pre-processing using CLAHE (Contrast Limited Adaptive Histogram Equalization), Blood Vessels (BV) extraction by using Kirsch's operator followed by feature extraction using Gray Level Co-occurrence Matrix (GLCM) detection of MAs and Classification using SVM. On evaluating the results, the proposed method got better performance than the existing method.***

Keywords: diabetic retinopathy, microaneurysms, glcm, svm classifier.

1. INTRODUCTION

The normal impact of vision misfortune in individuals is a result of diabetes which is the Diabetic retinopathy and mostly prompts visual deficiency among older folks who are working. Human with diabetes are at peril for causing diabetic retinopathy. Sickness increments when somebody has diabetes for longer time. Among all the Americans diagnosed with diabetes have certain phase of diabetic retinopathy which is about 40-45 percent, out of them only about partial are aware of DR. Women who are having diabetes in the course of pregnancy may have quick effect of diabetic retinopathy. These complexities can be forestalled if the analysis is done properly and regularly at least formerly a year. It is hard to identify the symptoms in the patients, who have DR, So that it would be late for giving effective treatment. Thus, for spotting and early medical involvement is vital. Normally, ophthalmologists observe DR based on characteristics, such as hemorrhages, Microaneurysms (MAs), texture and the expanses of the blood vessels. MAs are the first scientific sign to illustrate the diabetic retinopathy and specify it as red lesions. Agreeing to a written report, declared in [1, 2], half of 205,000 ophthalmologists are globally established in areas such as India, China, Russia, Brazil and USA. In summation, it is anticipated that the count of ophthalmologists will grow just 2%, while the diabetic patients will be 54% in 2030. For examination of each eye it takes 15 to 30 minutes. For this reason the work mainly concentrated on algorithm evolution and that algorithm is used to detect Microaneurysms in eye images. In general the people who suffered with diabetic, those peoples are need to require routine eye check up so that any eye issues are existing in or not can be recognized, if it has effected with any eye issue then the ophthalmologist give proper treatment to avoid blindness in early stage. Almost all the diabetic patients are often as possible way works intimately with the ophthalmologist. Most of the diabetic patients are having with the specific alignment. Diabetic retinopathy is dealt with in numerous routes relying upon the phase of the malady and the particular issue that requires consideration. The retinal specialist depends on a few tests to screen the movement of the ailment and to settle on choices for the fitting treatment. Normally, ophthalmologists observe DR based on characteristics, such as hemorrhages, Microaneurysms (MAs), texture and the expanses of the blood vessels. The first clinical sign of DR is Microaneurysms and Hemorrhages [14,15]. If the eye is effected with DR then the patient is having either microaneurysms or hemorrhages. MAs are the earliest clinically visible changes of diabetic retinopathy.

2. RELATED WORK:

According to [3, 4] in the color images, the lesion detection is done in two phases (1) Microaneurysms extraction and (2) Classification of MAs. A method for red lesion detection is represented in [5]. At this stage, to improve the image digital Curve lets transformation is applied and by manipulating the coefficients of transformation the lesions are detached, and then these red lesions are named as Candidates. In [6], MAs detection is gained over preprocessing the pixels. Detection is applied to the set of attributes like elevation; shape and size of the picture elements are measured. In paper [7] detection of MAs is done with coarse segmentation by using morphological operations and fine segmentation by using the SVM classifier. The problem for MAs detection is formed in [8]; the problem is finding regions of interest (blobs).To characterize these blobs many region descriptors are presented. In [9], there are two approaches for detection of MAs. They are: (1) an approach based on visibility and spatial location the MA candidates are brought away. (2) An approach of adaptive weighting which is based on spatial location and contrast the MAs are extracted. The results exhibited in this approach are based on selection of outcomes and individual detectors paper [10] introduces a

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singular method for MAs detection, which is based on multi overlapping and (RT) Radon Transform. On the preprocessing stage, to take out the background top-hat transform and averaging filter is applied [13]. In processing stage the total image is separated into sub-icons, and on every sub-image RT is applied for masking [11]. After masking and detection of ONH and blood vessels MAs are detected. And for performance evaluation 3 databases are applied. They are: (ROC) Retinopathy Online Challenge database, Mashhad database and Local database.

3. PROPOSED SYSTEM:

3.1 Pre-processing:

The Blood Vessel Feature based Classification (BVFC) is the proposed method and the lesion detection algorithm's performance depends on the quality of the retinal images. For identifying the pathetic character of the images there are so many elements. They are noisy, low contrast, non-uniform illumination, diffusion and variation in light reflection, differences in cameras and difference in retinal chrome. To slim down the image variations and to amend the image quality the Preprocessing stage is really important. Median filter is applied to green plane images to decrease the noise before a (CLAHE) Contrast Limited Adaptive Histogram Equalization is applied. Median filter is a nonlinear method which is used for reducing the noise. As random bit error occurs in the communication channel the noise will also be existed. In this process, adaptive histogram equalization is used and then the image is separated into regions and then histogram equalization is enforced on every region. To visible the hidden things in the image gray values is used. Then in the consecutive step, for contrast enhancement and to avoid over saturation of the same areas in retinal image CLAHE is applied as shown. To the result, median filter and CLAHE is applied to the original RGB images for correcting background variation and close ups of MAs is as depicted in the Fig.3.1 (a)–(c), respectively.

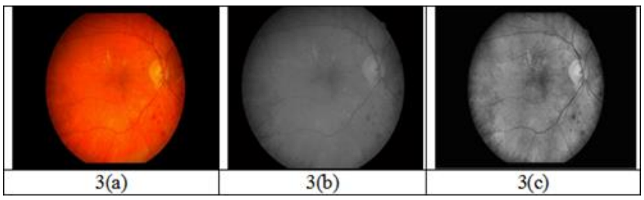

Fig 3.1: a) RGB Retina Image b) Median Filter c) CLAHE

3.2 BV Extraction using Kirsch's Template:

Kirsch formats are utilized for the extraction of veins from retinal picture Edge recognition is a procedure of distinguishing the pixel esteems to get much of the time and unexpected changes. The esteem 0 of pixel dark shows a dark pixel and the esteem 255 demonstrates a white pixel. Edge data of a specific and target pixel is checked by deciding the brilliance level of the neighboring pixels. In the event that there is no significant contrast in the brilliance levels at that point there is no probability of edge in the picture.

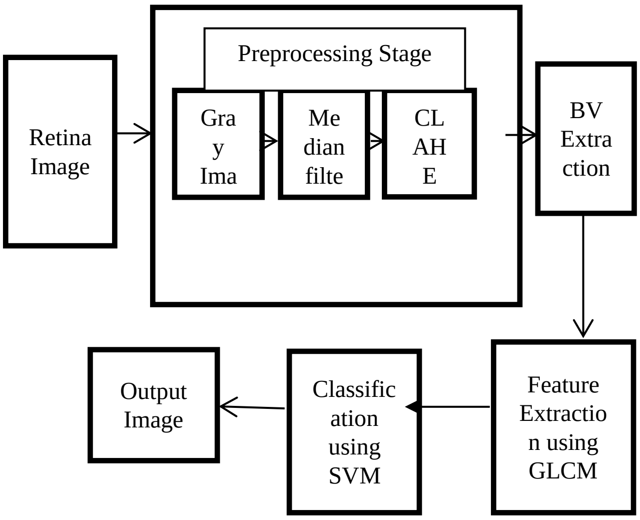

Fig 3.2: Proposed Method- BVFC

The portrayed strategy is most normal and central approach among all the accessible edge recognition calculations, for example, Prewitt, Sobel and so on. In this paper Kirsch format method is utilized for the extraction veins from retinal pictures. The Kirsch edge recognition calculation utilizes a solitary veil of size 3x3 and turns it in 45 degree augments through each of the 8 headings. The edge extent of the Kirsch administrator is ascertained as the most extreme greatness over all bearing. The network contains the data of a pixel and its neighbors. The Kirsch calculation identifies heading of the edge and additionally an edge. Kirsch calculation can viably connected and the result we can show in below fig 3.3 (a).

3.3 Feature Extraction by GLCM:

After preprocessing, to extract the features of resultant image and these features are evaluating the various calculations to give input to the SVM classifier. Here to extract the features, the authors are used Graly Level Co-occurrence Matrix (GLCM) algorithm to get the features of segmented images. The GLCM P [i, j] is characterized by first determining a relocation vector d= (dx, dy) [23]. Some of the GLCM features are explained the following:

1.ENERGY: Energy compares to the mean squared estimation of the picture ordinarily estimated as for the worldwide mean esteem. Energy of a picture restores the aggregate of squared components in the GLCM.

2.CONTRAST: The difference work upgrades the complexity of a image. Differentiation of a image restores a measure of the force differentiate between a pixel and its neighbor over the entire image.

3.CORRELATION: The task called connection is firmly identified with convolution. In connection, the estimation of a yield pixel is likewise processed as a weighted whole of neighboring pixels. The distinction is that the network of weights, for this situation called the relationship piece, isn't turned amid the calculation. The relationship task along these lines restores a measure of how associated a pixel is to its neighbor over the entire image.

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4.HOMOGENEITY: Homogeneity mirrors the consistency of a few pixels in a picture and communicates how comparative every one of them are. Homogeneity of picture restores an esteem that measures the closeness of the appropriation of components in the GLCM to the GLCM askew.

5.ENTROPY: Entropy is an element which measures the irregularity of gray level dispersion and the result we can show in below fig 3.3 (b).

The features extracted are fed to SVM classifier to classify the images for levels of DR in patients.

Fig 3.3 a) BV Extraction b) Feature Extraction

3.4 Classification using SVM:

For image classification in general (or) for DR we are using (SVM) Support Vector Machine classifier, which is a supervised learning method [12]. The hyper plane is used in decision boundary which isolates the negative and the positive data points, and this isolation should be maximal. The classifier equation is given as:

$$f(x) = w^T x + b \qquad \text{eq. (1)}$$

In eq. (1) "w" is the weight vector of the Hyper plane and "b" is the bias.

4. RESULTS & DISCUSSIONS

4.1 Performance Estimation:

We are using Sensitivity, Specificity and Accuracy for calculating the performance of a proposed algorithm. Sensitivity is defined as the probability of diagnosis, outcome is positive, which means the patient who has DR, is given as,

$$\text{Sensitivity} = \frac{TP}{FN+TP}$$

Where (TP) True Positives are the lesions which analyzed truly and (FN) False Negatives are the lesions which are falsely analyzed. Specificity is described as the probability of diagnosis result is negative, which means the patient is healthy and it is given as,

$$\text{Specificity} = \frac{TN}{FP+TN}$$

Where (TN) True Negatives are the ways which exactly eliminated and (FP) False Positives are the artifacts which incorrectly detected as lesions.

4.1 Result Analysis:

The Support Vector Machine is used for classification, here used SVM classification because our data has only two classes and also for greater accuracy and kernel function on small a data set train a binary SVM model. Based on the features came from the BVFC, we have to conclude that whether the given retinal image is suffered with diabetic retinopathy or not, that's why here we are used SVM classifier for classifying the extracted data. We have taken total 75 images, out of those 75 images, for training purpose we have taken 45 images. From these 45 train images, 10 images are normal i.e not affected with diabetic retinopathy and remaining 35 images are abnormal images i.e affected with diabetic retinopathy. For extraction of features like blood vessels, MAs the SVM classifier is applied along the training database. The tested dataset has containing 40 images, out of these 40 test images, 5 images are normal i.e not affected with diabetic retinopathy and other 35 images are abnormal i.e affected with diabetic retinopathy. These tested images are used SVM classifier. TABLE 1 shows the performance of the classifier and also show the graph representation in Fig 4.1 a) and b).

Method	No. of test images	Performance Parameters						
		TN	TP	FN	FP	Sensitivity (%)	Specificity (%)	Accuracy (%)
Harini R	30	23	6	1	0	98.63	94.84	96.65
BVFC Method	40	34	5	1	0	99.64	95.84	97.67

Table 1: Classifier Performance

In the classification solution, there are 39 test images with correct classification, and 1image with wrong classification. For the test images the performance of the classifier is calculated and accomplished as Sensitivity 99.64%, Specificity 95.84% and Accuracy 97.67%.

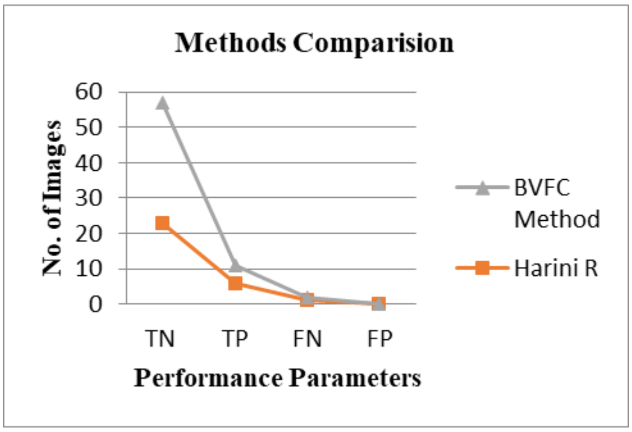

Fig 4.1 a) & b) Performance Parameters

5. CONCLUSION AND FUTURE WORK:

In this proposed method we introduced the methods one is blood vessels extraction using Kirsch's template followed by the feature extraction using GLCM and the result is given to the SVM classifier. Gathering up the images from DIARETDB0, DIARETDB1 databases which are publicly available. The images are divided by applying an SVM classifier. Established along the areas of blood vessels, MAs the results are needed; depending on those values the classification is done. And then, that the proposed algorithm attains 99.64% Sensitivity, 95.84%

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Specificity and 97.67% of Accuracy.

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