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Automatic Diagnosis Microaneurysm Using Fundus Images

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Abstract*—Early detection of DR diseases is important becauseof its potential for reducing the number of cases ofblindness around the world. Retinal photography for DR hasbeen promoted for decades for both the screening of thedisease and in landmark clinical research studies, such as theEarly Treatmentdamaging the microvasculature of retina in the eye.primary cause of visual impairment and blindness in diabeticpatients. As untreated Diabetic Retinopathy can cause permanent blindness, timely diagnosis and regular follow-ups are required to treat and control the rate of progression of the disease. Automated Diabetic Retinopathy detection systems have powerful tools for the screening of retinopathy as they are cost effective and efficient on large image database. This paper presents an automated system for the detection of Diabetic Retinopathy using fundus images, by extracting features such as Area of blood vessels, Area of microaneurysm and Texture Features. The selected significant features are trained and tested using Naive Bayes to classify the disease stages as normal, Background or Non-Proliferative Retinopathy (NPDR) and Proliferative Retinopathy (PDR).

***Index Terms*—Diabetic Retinopathy, Blood Vessels, ,microaneurysm, image databases, NPDR, PDR, Naive Bayes.**

I. INTRODUCTION

Diabetes Mellitus is a chronic disease is a group of metabolic diseases in which there are high blood sugar levels over a prolonged period.[2] Symptoms of high blood sugar include frequent urination, increased thirst, and increased hunger. If left untreated, diabetes can cause many complications.This alarming rate has prompted healthcare systems to devise measures for the proper management and control of the disease. Long term diabetes induces higher chances of a patient becoming affected by diabetic Retinopathy. Diabetic Retinopathy is persistent or acute damage to the retina of the eye. Ongoing inflammation and vascular remodeling may occur over periods of time where the patient is not fully aware of the extent of the disease. Frequently, retinopathy is an ocular manifestation of systemic disease as seen in diabetes or hypertension. In the manual screening process,
the specialist directly examines the eye or indirectly through images. The manual screening is time consuming.

In such scenario, the development of an automatic diagnosis system that can separate the normal and abnormal cases can significantly reduce the workload on the part of ophthalmologist. Therefore, in recent times, automatic Diabetic Retinopathy screening systems are gaining importance.

Digital images have been used in the image analysis and pattern recognition fields since long time. Automatic Diabetic Retinopathy screening systems deploy fundus image analysis to process those images using image processing and pattern recognition techniques to detect and analyze of severity of the disease.

Diabetic Retinopathy is a danger disease, which exhibits characteristic abnormal features and lesions at various stages of the disease. The main stages of retinopathy can be classified into Non Proliferative stage (NPDR) and Proliferative stage (PDR). The retinal image of a diabetic eye with anatomical features such as the optic disc and blood vessels and Fovea, and the abnormal features such as hemorrhages, Microaneurysms are as shown in Figure. 1 below.

Figure 1. Retinal lesions associated with diabetic retinopathy

In the normal eye, no lesions are present. Early manifestations of Diabetic Retinopathy occur in the form of microaneurysms, which occur as small protrusions of the blood capillaries and they appear as deep red spots on the

capillaries. When these microaneurysms burst, hemorrhages are formed. Bright-yellow colored Lesions such as hard occur as a result of fluid leaking into the retinal surface from the capillaries or from microaneurysms. Another bright white colored lesions, called the soft or cotton wool spots occur due to occlusions of the nerve fiber layer. Initially, at least one microaneurysm is seen. With the progression of the disease, the blood vessels become blocked and become short of blood supply. In an attempt to create new paths for blood supply, abnormal and fragile new blood vessels are formed on the surface of retina in the stage of Proliferative Retinopathy that might leak blood into retina causing permanent blindness. The three stages of Diabetic Retinopathy are as shown in the Figure 2 below.

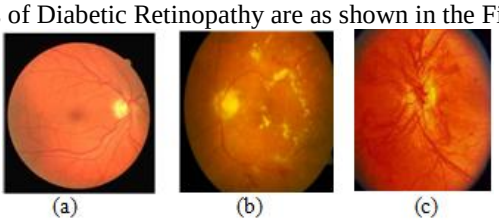

Figure 2. stages of retinopathy (a) normal (b) NPDR (c) PDR

II. RELATED WORK

Several approaches to diabetic retinopathy detection and classification are found in the literature. Techniques such as mathematical morphology, neural networks, region growing techniques, fuzzy C-means clustering,matched filters have been used. A two-dimensional matched filtering technique for Blood vessels detection was proposed to detect the presence of piecewise linear segments of vessels by rotating 12 different kernel templates at several orientations [1]. Vascular abnormalities were detected by feature extraction and Gabor filter bank outputs at several finer scales were used to represent energy variations by scale-angle method to classify disease severity as mild, moderate and severe diabetic retinopathy [2]. Blood vessel detection using top hat transform and watershed transform using mathematical morphology is described in [3]. Gray level variations of the and morphological reconstruction methods were used in the extraction of [4]. Automatic and cotton-wool spots detection system is developed in [5]. Automated system for grading the severity of was proposed in [6]. were detected by top-down segmentation method followed by local thresholding by combining edge detection techniques and region growing. A polar coordinate system was used in the grading of severity of . Classification of Diabetic Retinopathy stages as normal, mild, moderate, severe background retinopathy and as Proliferative by Acharya in [7]. The feature extraction was done using Higher Order Spectra (HOS). Area and perimeter from the RGB components of the blood vessels were used as features in grading the severity of retinopathy using a feed forward neural network [8].Features such as area of and the area of blood vessels together with texture parameters were input to neural network to grade the images into normal, Non-Proliferative Retinopathy and Proliferative Retinopathy by Nayak et al. [10].

This paper presents an automatic Diabetic retinopathy severity classification system using image processing techniques. Input images are classified as belonging to one of the stages of retinopathy, based on the feature vector extracted using multiclass Naive Bayes as classifier. It involves the segmentation of retinal blood vessels and . Feature extraction phase consists of calculating area of the blood vessels, area of the and texture features. Out of all the features extracted few of the significant features are selected to form a feature vector that is input to Naive Bayes (NAIVE BAYES) classifier.

NAIVE BAYES is designed to classify the images into normal, NPDR and PDR stages. The paper is organized as follows. Section I covers introduction. In Section II, survey of related work is presented. Section III describes the proposed method. In section IV, results are presented followed by conclusion in section V.

III. PROPOSED METHOD

The block diagram for the Retinopathy detection and the classification is as shown in the Figure 3. The input retinal images are preprocessed in the first step. The segmentation of blood vessels and is done. The area of these features and the textural features are measured. Feature selection is carried out to extract only the significant features Texture features for classification into normal, NPDR and PDR stages.

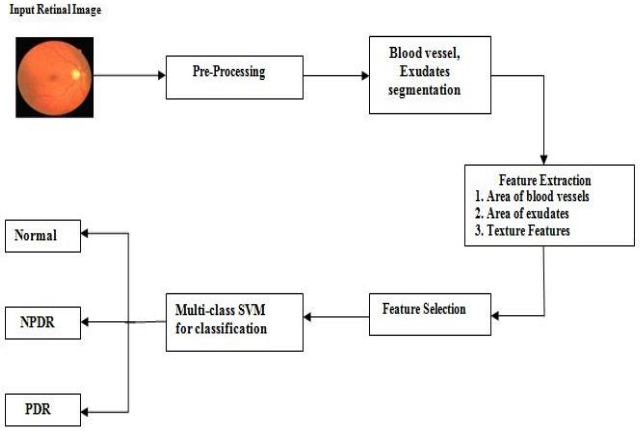

Figure 3. Block Diagram of the automated detection diabetic retinopathy detection system

A. Blood Vessels Detection

Vascular abnormalities are important indicators of diabetic retinopathy. The blood vessel segmentation and feature extraction is utilized in the current work. The images are usually lower in contrast and significant proportions of noise exist in the images. A preprocessing step comprises of noise removal using filtering techniques and homogenization of the non-uniform background. An averaging filter of dimensions 3x3 is used for noise smoothing. Further smoothing is done by Gaussian filtering and a shade correction method based on subtraction method is applied to eliminate background variations. A larger arithmetic filter is used to generate the background image. This image is subtracted from the Gaussian filter output to generate a shade corrected image. The image is enhanced by Contrast Limited Adaptive Histogram Equalization (CLAHE).Top-Hat transform is used to enhance the blood vessels. The enhanced image consists of vessels with the background which is eliminated by thresholding. The noise in the images is eliminated by morphological filtering methods such as opening by reconstruction and opening-closing by reconstruction. The circular border is removed by performing an AND operation with the mask image. This results in the final segmented blood vessel image. The block diagram of the blood vessel detection method is as shown in Figure. 4 below.

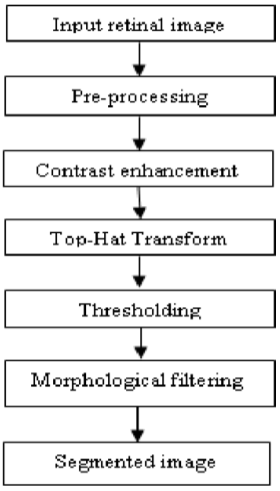

Figure 4. Block diagram for blood vessel

B. Detection of Hard

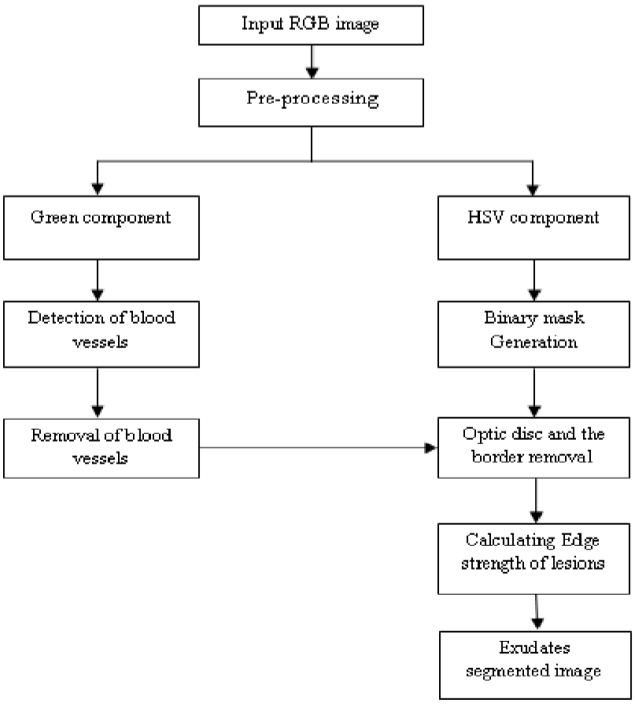

Figure 5. Block diagram for detection of

The block diagram of detection is as shown in the Figure 5 above. Hard were detected using image processing operations. The Green component of the image is extracted as the contrast of retinal lesions and vessels is good compared to the red and blue channels. Blood vessels are detected using kirsch operator. The edge detected image is reconstructed using morphological reconstruction. This image is subtracted from the green component image to remove blood vessels. The gray component of the image is derived to generate an intensity image in the HSV color space. Binary Mask of the image is generated. Image is median filtered to generate a background image. The reconstructed median filtered image is

subtracted from the original image to generate a segmented image which after the AND operation with the binary mask is used to remove the optic disc and border. The edge strength of the from the candidate lesions enhanced image is found to extract the final image.

C. Multiclass NAIVE BAYES for Diabetic retinopathy severity Classification

Naive Bayess (NAIVE BAYES) are a set of supervised learning tools applied for data classification and regression. NAIVE BAYES model maps the training samples that are the points in features space into different categories which are clearly separated with the widest gap in between them. The testing samples are mapped to the same feature space and classified as belonging to any of the classes.

NAIVE BAYES constructs an optimal hyper plane that would maximize the margin of separation between the classes. The feature vectors that lie close to the margin are called the support vectors. Figure 6 depicts the Naive Bayes classifier with the optimum hyperplane. A binary NAIVE BAYES finds an optimum hyper plane which separates the feature vectors of the two classes with largest margin from the hyper plane. The separating hyper plane is of the form w.x+b=0, where w is the norm. If the data is linearly separable, the maximum margin of separation is found by the minimization of the function

$E=\| w^2 \|$.

If the training data is non-linear, then input space would be mapped to a higher dimensional feature space H through the mapping φ. As an extension to binary NAIVE BAYES as classifier, multi class approach to classification problem is developed. The general methods are one-against-one, one-against-all and global method. In the current work, one-against-all approach is used, in which a collection of binary classifiers is used, and one classifier separates a class from the remaining ones with the largest margin. The training data is chosen to be statistically significant, such that during training the training set analyzes the data into different classes.

D. Image datasets

The input images are acquired through DIARETDB0 [10] and DIARETDB1 [11] databases. These databases have been used for analyzing the performance of algorithms used for automateddiagnosis of diabetic retinopathy. The images were acquired fromKuopio general hospital. The DIARET DB0 consists of 130 images of which 110 images contain retinopathic lesions. The DIARETDB1 consists of 89 images of which 5 of the images are normal while 84 images contain the signs of retinopathy. The input images are classified as belonging to normal, NPDR or PDR classes using multiclass NAIVE BAYES classifier.

E. Parameters for Performance Evaluation of the classifier

The evaluation of the performance of the classifier is done by calculating the parameters such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP is the number of abnormal images classified as abnormal by the screening system. TN is the number of images that are really normal and classified as normal by the screening procedure. FP is the number of normal images that are predicted to be abnormal and FN is the number of abnormal images, classified by the procedure to be normal. Using these parameters, Sensitivity, Specificity and accuracy are calculated.

Sensitivity is the measure of percentage of abnormal images classified by the screening procedure.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100$$

Specificity is defined as the percentage of normal images classified by the system. Accuracy in percentage is the measure of

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100$$

Accuracy is the percentage of correctly classified normal and abnormal images.

$$\text{Accuracy} = \frac{TP+TN}{(TP + FN+TN+FP)} \times 100$$

IV. RESULTS

Table I shows the results for classification into three categories such as normal, NPDR and PDR after training and testing with images of each category.

Table I. Results for classification into normal, NPDR andPDRcategories

TP	TN	FP	FN	Sensitivity (%)	Specificity	Accuracy
8	5	0	2	85	97.3	89.6

Table II. Calculation of TF, TN, FP and FN parameters

Results for sensitivity, specificity and accuracy calculations are as shown in table II.

V. CONCLUSION

DR has been studied by different groupsin the past decade, few studies have used a top-down approachlike the one we propose.An automated system for diabetic retinopathy detection has been presented. The method extracts blood vessels and for grading the severity of the diabetic retinopathy. Image processing operations and the pattern recognition techniques have been investigated on benchmark retinal image databases. The Specificity, sensitivity and accuracy found are 97.3%, 85% and 89.57% respectively.

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