Diabetic Retinopathy Detection Using Image Processing

Mr. D. K. Kirange
Dept. of Computer and IT, J T Mahajan College of Engineering,
Faizpur, Tal, Yawal, Dist. Jalgaon, India

Smt Shubhangi D Patil
Department of Information Technology
Government Polytechnic Jalgaon

Mr Kanchan S Bhagat
Dept. of Electronics and Telecommunications,
J T Mahajan College of Engineering,
Faizpur, Tal, Yawal, Dist. Jalgaon, India

***Abstract*: In the modern world, diabetic etinopathy (DR) has become one of the most severe complication prevalent among diabetic patients. The success rate of its curability solemnly depends on the early stage diagnosis or else will lead to total blindness. Here we have proposed a novel method for the automated identification and grading of diabetic retinopathy in fundus images based on machine learning technique. Approach employs a unique sequential execution of image enhancement, noise removal, blood vessels segmentation followed by optic disc ellimination, exeudates detection, microannynysms and haemorhages detection to extract fundus image features like area of Microannenysms, exeudates and haemorhages, together with texture feature analysis using Gabor and statistical features. Finally features selected are passed into the well-known support vector machine (SVM) and neural network classifier which classifies the images into normal and abnormal classes**

1. Introduction

The World Health Organization (WHO) estimates that there are currently 347 million people suffering from diabetes and projects that this disease will be the seventh leading cause of death worldwide in 2030. Over the years, patients with diabetes tend to show abnormalities in the retina, developing a complication called Diabetic Retinopathy (DR). DR is one of the most serious diseases affecting the eye, and it is considered the most common cause of blindness in adults between 20 and 60 years of age. Studies show that people above the age of 30 years that suffer from diabetes for more than 15 years have 78% chance of also having DR. This rate rises to 97% for people below the age of 30 years that suffer from diabetes for the same period of time. Thus, DR affects adults in working age, being a disease that is strongly associated with inability to work, causing significant costs to institutions and governments. It is estimated that the U.S. government has an annual cost of 500 million dollars in the treatment of visual impairments originated by diabetes.

In Fig. 1 is shown a fundus image captured in a noninvasive way, containing microaneurysms and hemorrhages.

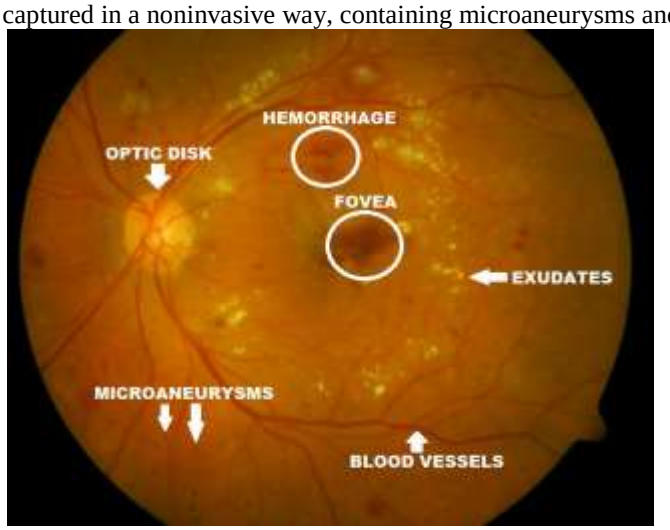

Figure 1. Fundus image containing microaneurysms and hemorrhages

As shown in Fig. 1, the microaneurysms are small red spots dispersed on the blood vessels wall. On the other hand, the hemorrhages have a larger size, and are characterized by red swellings. The manual detection of these red lesions is made by ophthalmologists and is a slow and errorprone activity. Some lesions have a very small size and may go unnoticed even by trained specialists. In addition, manual detection may be considered unfeasible in government programs for mass screening of diabetic populations, since it would require a huge amount of doctors and examinations. Thus, it is evident the need of methods for automatic detection of red lesions in fundus images.

In short, DB is caused by a change in the structure of the blood-vessels of the human eye"s retain. The retinastructure will be a thin, inward coating at rear end of human eyes that is very much dependent on the light. The harm is caused by an expansion in blood's sugar level of the glucose contents which can hurt veins/capillaries. At the point/juncture when these veins-capillaries thicken-become big, they can create spills, which then gives rise to the human eye's vision loss. The 4 categories of DR could be summarized as

- Mild-Initial stage,
- Moderate-Mid way stage,
- Severe/nonproliferative-pre final stage &
- Proliferative-final stage.

2. Review of Related work in Diabetic Retinopathy Detection

There are several approaches to diabetic retinopathy detection and classification. Many techniques based on mathematical morphology, neural networks, pattern recognition, region growing techniques, fuzzy C-means clustering, Gabor filter banks are available from the literature. Blood vessels were detected using two-dimensional matched filter [1]. Automatic extraction of the vasculature was done using a sparse tracking method [2]. Automatic detection and the classification of abnormalities on the vascular network was done by using Gabor filter bank outputs at several finer scales to obtain a scale and angle method of representation of energy variations, to classify the mild, moderate and severe stages of retinopathy [3].

Sinthanayothin developed a method based on recursive region growing methods and Moat operator to detect Hemorrhages, Microaneurysms and exudates [4]. Several Optic disc detection methods were proposed. Principal Component Analysis (PCA) based approaches were derived where the candidate regions for optic disc were derived by clustering of brighter pixels.PCA was applied to calculate the minimum distance between the image and its projection to find the optic disc center [5]. Optic Disc detection was also done using Hough Transform [6]. Microaneurysms and hemorrhages were detected using morphological operations with a structuring element and tophat transformation [7]. Mahalanobis classifier was used to identify hemorrhages and microaneurysms [8]. Image processing techniques in combination with pattern recognition techniques were used to detect microaneurysms and hemorrhages in fundus images [9].

Higher Gray level variations of the exudates and morphological reconstruction methods were used in the extraction of exudates [10]. Automatic exudates and cotton-wool spots detection system is developed in [11]. A neural network based approach was used exudates detection [12]. A fuzzy C-means clustering method [13] and computational intelligence based approach was proposed for detection of exudates [14]. Acharya [15] classified Diabetic Retinopathy stages as normal, mild, moderate, severe and proliferative. The feature extraction was done using Higher Order Spectra (HOS).A multi-layer perceptron was used to classify normal and diabetic retinopathy stages [4].

Kahai developed a decision support system, using bayes optimality criterion to detect Microaneurysms that enables the early detection of diabetic retinopathy [16]. Area and perimeter calculated from the RGB components of the blood vessels were used as features to classify normal, mild, moderate, severe and proliferative stages of retinopathy using a feed forward neural network [17]. Nayak et al. used features such as area of exudates and the area of blood vessels together with texture parameters and features are input to the neural network to classify images into normal, Non-Proliferative Retinopathy and Proliferative Retinopathy [18]. Automatic classification into normal, mild, moderate, severe and proliferative classes of Diabetic Retinopathy was done by calculating the areas of several features such as, hemorrhages, microaneurysms, exudates and blood vessel with support vector machine as classifier [19]. Automated diagnosis system is developed to detect retinal blood vessels, and pathologies, such as exudates and microaneurysms together with certain texture properties using image processing techniques. The area of lesions and texture features are then used to construct a feature vector that is input to the multiclass support vector machine (SVM) for classifying images into normal, mild, moderate, severe and proliferative categories [20].

Performance of the following feature extraction techniques is evaluated using well known SVM and Neural Network classifier. The diabetic retinopathy images are classified as

Grade – 0: No apparent retinopathy
Grade – 1: Mild – NPDR
Grade – 2: Moderate – NPDR
Grade – 3: Severe – NPDR
Grade – 4: PDR

Performance is evaluated for following different features.

a. GLCM Features
b. Gabor Features
c. Area of Microannenysms, haemorhages and exeudates
d. Local Binary Pattern

3. Datasets

IDRiD DATASET FOR DR GRADING

In this paper, IDRiD (Indian Diabetic Retinopathy Image Dataset [9] is used for detection and grading of diabetic retinopathy. This database is the representative of an Indian population. Moreover, it is the only dataset constituting typical diabetic retinopathy lesions and also normal retinal structures annotated at a pixel level. This dataset provides information on the disease severity of diabetic retinopathy, and diabetic macular edema for each image. This makes it perfect for development and evaluation of image analysis algorithms for early detection of diabetic retinopathy.

There may be a presence of venous beading, retinal neovascularization which can be utilized to classify DR retinopathy in one of the two phases known as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) as shown in Figure 1a and 1b. DME is a complication associated with DR in which retinal thickening or accumulation of fluid can occur at any stage of DR. The risk of having DME is classified into no risk and two probable risks (illustrated in Figure 1c and 1d respectively). The determination of DR and DME severity based on criteria given in Table 1. It is essential to decide the need for treatment and follow-up recommendations.

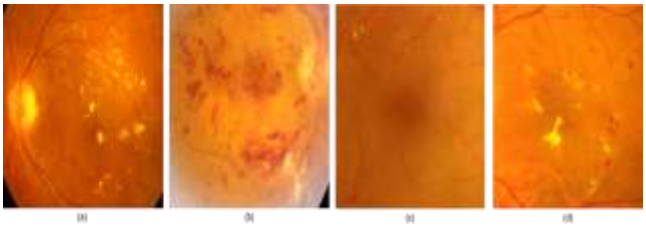

Figure1: Phases of diabetic Retinopathy

The dataset for Diabetic Grading consists of it consists of

1. Original color fundus images (516 images divided into train set (413 images) and test set (103 images) - JPG Files)
2. Groundtruth Labels for Diabetic Retinopathy and Diabetic Macular Edema Severity Grade (Divided into train and test set - CSV File)

Disease Severity Level	Findings
Grade – 0: No apparent retinopathy	No visible sign of abnormalities
Grade – 1: Mild – NPDR	Presence of Microaneurysms only
Grade – 2: Moderate– NPDR	More than just microaneurysms but less than severe NPDR
Grade – 3: Severe – NPDR	Any of the following: > 20 intraretinal hemorrhages Venous beading Intraretinal microvascular abnormalities no signs of PDR
Grade – 4: PDR	Either or both of the following: Neovascularization Vitreous/pre-retinal hemorrhage

Table 1: Diabetic Retinopathy Grading

4. Detection and Grading of Diabetic Retinopathy

We intent to develop a system for detection and grading of diabetic retinopathy using machine learning. Such system needs to be able to detect the presence of diabetic retinopathy as well as severity of the disease. We believe that diabetic retinopathy detection and grading based on proposed GLCM and Gabor features with area of microanenysms and hemorrhages is the appropriate solution. In our work, we have classified the severity of the diabetic retinopathy images into five grades as

Grade – 0: No apparent retinopathy
Grade – 1: Mild – NPDR
Grade – 2: Moderate – NPDR
Grade – 3: Severe – NPDR
Grade – 4: PDR

To be able to correctly identify the type of diabetic retinopathy disease well established features such as Gabor, GLCM, LBP will be used to create the offline features database. The area of microanenysm and hemorrhages is also used as a feature for classification. The performance of the system is evaluated for SVM and neural network classifiers.

The proposed methodology for detection and grading of Diabetic Retinopathy is depicted below:

1. Select Training Image Directory
2. Training Preprocessing : Median Filtering for Noise Removal
3. Compute the area of Microanesyms and Haemorhages

a. Apply adaptive histogram equalization for contrast enhancement
b. Noise removal using ‘log’ filter
c. Optic Disc Removal

i.Blood Vessel Extraction Using Kirsch's Templates
ii. Removing blood vessels from the original image using morphological close operation

iii. Binarize the resultant image and apply different morphological operations to find the biggest circle and removing it from the image.

d. Exeudates Detection using morphological dilate, erosion and reconstruct methods.

e. Microanesyms image is obtained by removing blood vessels and exeudates from the preprocessed image

f. Binarise the Microanesyms image and compute the area using regionprops. If the area is less than 5 then it is considered as Micronesyms and if the srea is greater than 500 then it is considered as Haemorhages

4. Local Binary Pattern (LBP), Statistical and Gabor features are computed for all training images.

5. Feature vector matrices are constructed by combining Local Binary Pattern (LBP), Statistical and Gabor features with area of Microanesyms and Haemorhages separately.

6. Neural network and SVM classifiers are trained using features vector matrices.

7. After preprocessing and feature extraction of test images, performance of SVM and Neural networks classifiers is evaluated for detection and grading of diabetic retinopathy.

5. Evaluations and Results

The performance of SVM and Neural Network classifiers have been evaluated by considering different number of training images. Four parameters are used for evaluating performance of the algorithm. Those are accuracy, precision, recall and F measure. These parameters are defined using 4 measures True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)

True Positive: DR detection coincides with actual labelled data

True Negative: both classifier and actually labelled absence of DR

False Positive: system labels a healthy case as an DR one

False Negative: system labels DR image as healthy Accuracy: Accuracy is the ratio of number of correctly classified cases, and is given by

Accuracy= (TP+TN) / N

Total number of cases are N

Precision is the fraction of retrieved images that are relevant to the query. Precision takes all retrieved images into account, but it can also be evaluated at a given cut-off rank, considering only the results returned by the system

Precision is defined as

Precision = TP/ (TP+FP)

Recall is the fraction of the relevant umages that are successfully retrieved. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

It is trivial to achieve recall of 100% by returning all documents in response to any query. Therefore, recall alone is not enough but one needs to measure the number of non-relevant documents also, for example by also computing the precision.

Recall is defined as

Recall= TP / (TP+FN)

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall. In our case, F1 score is 0.701.

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

We have evaluated the performance of diabetic retinopathy detection and grading on IDRiD (Indian Diabetic Retinopathy Image Dataset

Performance of the following feature extraction techniques is evaluated using well known SVM and Neural Network classifier

a. GLCM Features

b. Gabor Features

c. LBP Features

The performance is evaluated by considering 70% data as the training data. The results are depicted in table 10. To evaluate the performance we have used Accuracy, Precision, Recall and F measures.

Accuracy		
	Neural Network	SVM
Gabor	65.9574	74.4681
Statistical	43.2624	57.4468
LBP	51.773	51.0638
Precision		
	Neural Network	SVM
Gabor	0.6751	0.803
Statistical	0.4493	0.5634
LBP	0.5314	0.4983

Recall		
	Neural Network	SVM
Gabor	0.6911	0.815
Statistical	0.4342	0.5626
LBP	0.5291	0.4829
Fmeasure		
	Neural Network	SVM
Gabor	0.683	0.809
Statistical	0.4416	0.563
LBP	0.5303	0.4905

Table 2 Performance Evaluation of Diabetic Retinopathy Grading for 70% training data

As depicted in table 2, the Gabor features with SVM classification can result in better recognition accuracy for GLCM and LBP.

6. Conclusion and Future scope

Automated diabetic retinopathy detection and grading is very important to improve the accuracy of manual evaluation and inspection of the disease. In the modern world, diabetic etinopathy (DR) has become one of the most severe complication prevalent among diabetic patients. The success rate of its curability solemnly depends on the early stage diagnosis or else will lead to total blindness. Here we have proposed a novel method for the automated identification and grading of diabetic retinopathy in fundus images based on machine learning technique. Approach employs a unique sequential execution of image enhancement, noise removal, blood vessels segmentation followed by optic disc ellimination, exeudates detection, microannynysms and haemorhages detection to extract fundus image features like area of Microannenysms, exeudates and haemorhages, together with texture feature analysis using Gabor and statistical features. Finally features selected are passed into the well-known support vector machine (SVM) and neural network classifier which classifies the images into normal and abnormal classes. The diabetic retinopathy images are also classified into five severity classese as Grade – 0: No apparent retinopathy, Grade – 1: Mild – NPDR, Grade – 2: Moderate – NPDR, Grade – 3: Severe – NPDR, Grade – 4: PDR,
Real time and publicly available database analysis shows really encouraging performance metrics of the proposed method using SVM in terms of accuracy.

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