

Diabetic Retinopathy Detection System from Retinal Images

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ABSTRACT

Diabetes Mellitus is a disorder in metabolism of carbohydrates, and due to lack of the pancreatic hormone insulin sugars in the body are not oxidized to produce energy. Diabetic Retinopathy is a disorder of the retina resulting in impairment or vision loss. Improper blood sugar control is the main cause of diabetic retinopathy. That is the reason why early detection of retinopathy is crucial to prevent vision loss. Appearance of exudates, microaneurysms and hemorrhages are the early indications. In this study, we propose an algorithm for detection and classification of diabetic retinopathy. The proposed algorithm is based on the combination of various image-processing techniques, which includes Contrast Limited Adaptive Histogram Equalization, Green channelization, Filtering and Thresholding. The objective measurements such as homogeneity, entropy, contrast, energy, dissimilarity, asm, correlation, mean and standard deviation are computed from processed images. These measurements are finally fed to Support Vector Machine and k-Nearest Neighbors classifiers for classification and their results were analysed and compared.

KEYWORDS: *Diabetic Retinopathy, Retinal Images, Support Vector Machine, k-Nearest Neighbors*

I. INTRODUCTION

The complication of diabetes that affects the eyes is fewer than 1 million cases per year (India). Diabetic Retinopathy (DR) is the main cause for loss of vision. It is the cause of loss of vision among people with Diabetes Mellitus (DM). Patients having DM are more times prone to blindness than without DM. It's a major concern in which, this disease has directly major influence in the eyes. As we know that iris, retina, cornea, optic nerve, nerve fibers are the major and important parts of the eye and retinopathy causes the change in the level of sugar in blood in the retina which further causes veins to burst. The bursting of capillaries or veins leads to bleeding and thus leading to vision loss. When the level of sugar is high in blood flowing through blood veins, blood vessels in retina gets highly damaged. People with diabetes are more likely to get attacked with the disease. Early symptoms include floaters, blurriness in vision, difficult to perceive colors and dark areas of vision.

DR can be treated effectively only in its early stages and thus early detection is very important through regular screening. Automated screening is highly required so that manual effort gets reduced as, expense in this procedure is quiet high. In order to detect retinopathy on early basis, there are several Image Processing techniques which includes Image Enhancement, Segmentation, Image Fusion, Morphology and Classification has been developed on the basis of features such as blood vessels, exudates, hemorrhages, and microaneurysms. Since fundus imaging is a common clinical procedure it is used to determine patient suffering from diabetic retinopathy.

Computer-Assisted Diagnostic (CAD) plays a vital role in automatic analysis of retinal images and hence, there is a need to develop it. Development of CAD system have raised a need of image processing tools that provide fast and reliable. Segmentation of these retinal anatomical structures is the first step in any automatic retinal image analysis.

The existing manual system is really primitive wherein a professional doctor determines whether he/she is suffering from DR on the basis of their retinal scan report. This is done by the doctor on the basis of his/her medical studies. In this paper, our task is to detect the main components of retinal images of people suffering from DR and classifying the stage of the disease. K-nearest neighbor classifier is also implemented to contrast the results obtained with support vector machine classifier.

The rest of the paper is organized as follows: Section II introduces diabetic retinopathy. Section III gives survey of different existing works on DR. Section IV discusses the methodology of the proposed system. Section V discusses the experimental results of proposed system. Finally, the conclusion of the paper is included in Section VI.

II. DIABETIC RETINOPATHY

Number of diabetic patients suffering from DR is increasing every year. DR is one of the most chronic disease, which makes the key cause to vision loss. The disease is local in its early stages; it does not affect the whole retina; thus causing gradual vision impairments. The major risk factor in this

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disease is the level of blood sugar. Due to high level of sugar in blood, blood vessels in retina are heavily damaged.

Various lesions like microaneurysms, hemorrhages, hard exudates, blood vessels are explained as: Microaneurysms are out-pouching of the retinal capillaries, appearing as small red dots on the fundus image. They appear as small bulges developed from weak blood vessels. They are the earliest clinical sign of DR. Leakage of oily formations from the poor end blood vessels are known as exudates. Hard Exudates are well-circumscribed, shiny white or cream deposits located within retina. They indicate accumulation of fluid in the retina and considered sight threatening if appear close to the macula center. They are generally seen together with Microaneurysms. At every different retinopathy stage their shape and size varies; as it starts emerging, the DR is termed as moderate non-proliferative DR [36]. When retinopathy increases with time, blood vessels in retina get blocked by micro infarcts known as soft exudates. Presence of these three abnormalities is termed as severe non-proliferative diabetic retinopathy. Hemorrhages may take various shape and sizes depending on their location within retina. Most common DR hemorrhages are dot hemorrhages.

III. RELATED WORKS

[4], presents an approach for localizing different lesions and features in retinal fundus image. The authors proposed a constraint in detecting optic disk. Blood vessels, exudates, microaneurysms and hemorrhages were detected using different morphological operations which success rate of 97.1% for disk localization.

[23], presents SVM classifier for the classification of the disease. They proposed a methodology for detecting optic disc, blood vessels and exudates and then feature extraction is carried out followed by classification. This yielded an average accuracy of 94.17%. The problem in the proposed method of exudate classification was less that was mainly due to false intensity computation features.

V. Ramya *et al* [24] proposed a method for the recognition of DR using SVM classifier. The focus of this paper is on distinguishing patients with PDR and NPDR. The proposed methodology begins by pre-processing techniques: median sifting and histogram equalization followed by feature extraction. Based on the extracted features levels of DR were classified using SVM. The proposed calculation accomplished overall recognition rate of 84% based on hemorrhages.

An approach for early detection of DR from fundus images presented in [16]. Starting with pre-processing of raw retinal fundus images using extraction of green channel, histogram equalization, image enhancement and resizing techniques. For evaluation of the results, is done by considering the area, mean value and standard deviation for the extracted features. Detection of DR is done using machine learning techniques. From the results obtained, they showed that exudate area was the best feature out of blood vessel and all other features for DR detection, which finally concludes that exudate is one of the major feature responsible for diabetic retinopathy.

Sahana Shetty *et al* [25] have presented an approach for detecting Diabetic Retinopathy using SVM. The author's study began by pre-processing, then eliminating optic disk, and separating vascular tissue of damaged area of the retina. Mathematical morphology methods were carried out to detect dark lesions then followed by feature extraction. Extracted features were classified using SVM. Performance of SVM showed better results than using image processing with AUC above 90%.

Ahmad Z. F, Muhammad F. *et al* [26] and S Deva Kumar and Gnaneswara Rao Nitta *et al* [32] have taken up GLCM as method for feature extraction and SVM for classification. [32] Includes CLAHE, Kirsch's operator for detecting blood vessels, in [26, 32] features obtained by GLCM. SVM classifier is used to classify DR [26, 32]. Comparing [26, 32], accuracy [32] was shown better compared to [26].

A method of an automatic detection and classification of DR system is been proposed in [30, 33]. For detection [30] uses, Circular Hough Transform and image processing while morphological operations are used in [33]. Textural features and HOG, SURF features are extracted [30, 33]. The authors use Support Vector Machine in order to classify the retinal fundus image as normal, NPDR and PDR.

[2, 5] used ANN for the classification of the disease. [2] used the classifier for classifying the image as normal and abnormal and [5] for classifying the image as moderate, mild and severe stages. However, one of the methods from [5] fails because of the non-detection of soft exudates that occurred in the optic disk because of its removal.

IV. METHODOLOGY

In this section, we discuss the proposed methodology of the general Diabetic Retinopathy Detection System. The proposed system comprises of two phases:

- Training Phase
- Testing Phase

The Training Phase comprises of Pre-processing, Segmentation of retinal features, Feature Extraction, Storing features in the database and Training. Testing Phase comprises of loading the test image, Pre-processing, Segmentation of Retinal features, Feature extraction and Classification as normal, moderate or severe, done using SVM and k-NN classifiers.

A. Training Phase

This step deals with training the system for diabetic retinopathy recognition. SVM and k-NN will be used in this case. Each image is unique in dataset. Each retinal fundus image was pre-processed. The pre-processing steps applied on each fundus image are explained below.

1. Pre-Processing

Image pre-processing is the initial step in DR detection system. Pre-processing should be applied before feature extraction. Preprocessing steps applied on the image are:-

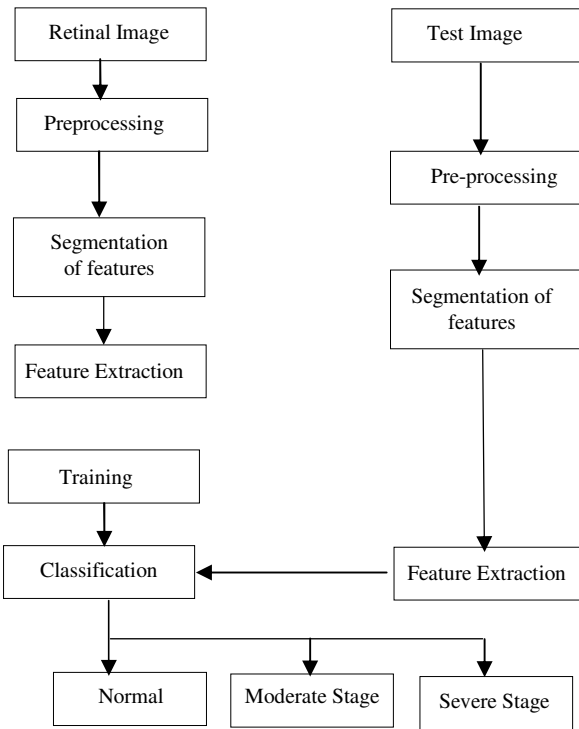
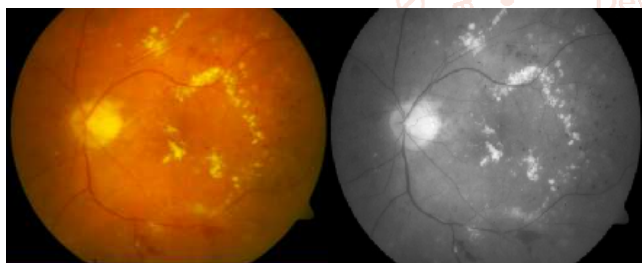


Figure 1: System Architecture

A. Gray scaling:

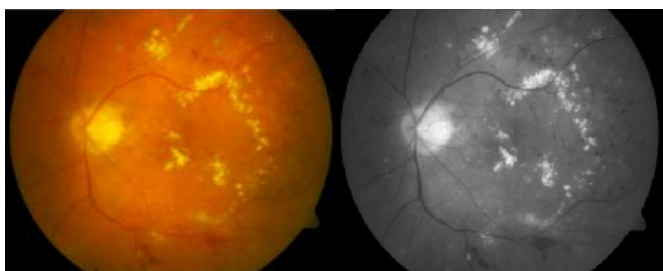
The training phase includes gray scale processing as shown in figure 4. In order to convert a color to gray representation, RGB values are obtained first by gamma expansion and to which 30%, 59%, 11% of RGB are added together whose result is some luminance value regardless of the scale employed. To get the final gray representation, the previous result is gamma compressed.



a. Original Image b. Gray scale Image
Figure 2: Gray scaling

B. Green Channel:

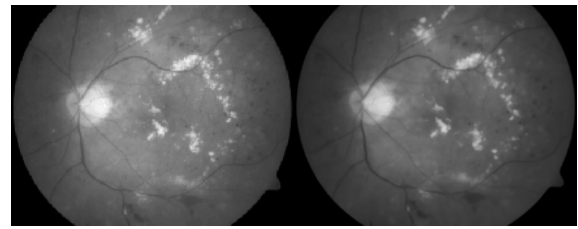
Since RGB image is the input image, any one channel (red, green, blue) can be used. Hence RGB channels are separated from RGB image. Green channel has a good contrast than red and blue channels. Since green channel gives a better contrast; therefore, used for detection purpose hence, this channel is considered as natural basis for automated detection algorithms.



a. Original Image b. Green channel
Figure 3: Green channel

Filtering:

Median filter is used to remove outliers without affecting the sharpness of the image. It also reduces the intensity variation between the pixels. Median filter replaces the center value of the window with median value.



a. Green channel b. Median Filter
Figure 4: Filtering

2. Segmentation of Features

In order to detect NPDR we have implemented two processes to extract some important features.

A. Detection of Blood Vessels:

Each image is unique in dataset. Each retinal fundus image was pre-processed. The pre-processing steps applied on each fundus image are explained below. Through the process of image processing detection of blood vessels is an important step for the identification of DR. Since green channel has highest contrast between the background and the blood vessels, it is carried out first for efficient segmentation followed by adaptive histogram equalization. Adaptive histogram equalization improves the contrast. To smooth the background and highlighting blood vessels alternate morphological closing and opening operations is applied. Subtraction of image after histogram equalization from the image after alternate morphological opening and closing outputs image with no optic disc. The output after the subtraction operation is inverted to get binary image using bitwise operation. Final output is the detected blood vessels as shown in Figure 5.

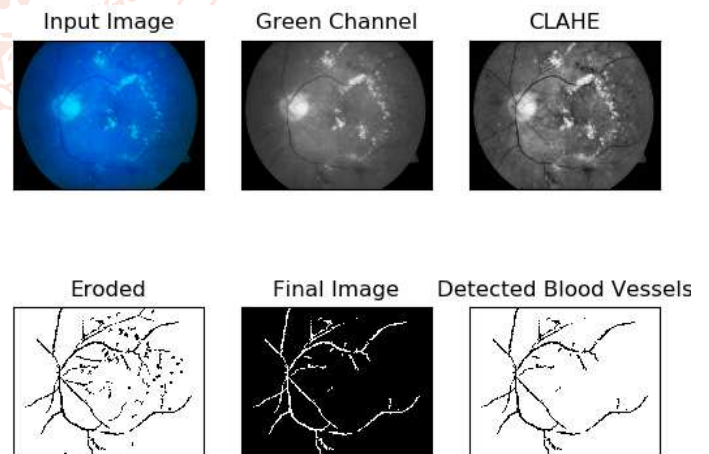


Figure 5: Blood vessel extraction system

B. Detection of Exudates:

The retinal fundus image is pre-processed first. In order to detect exudates, steps similar to detection of blood vessels green component of RGB image is extracted followed by adaptive histogram equalization, to further enhance the features of the image. This highlights the exudates. Morphological image processing technique dilation is performed followed by thresholding. Finally, by performing a morphological opening, exudates are detected as shown in Figure 6.

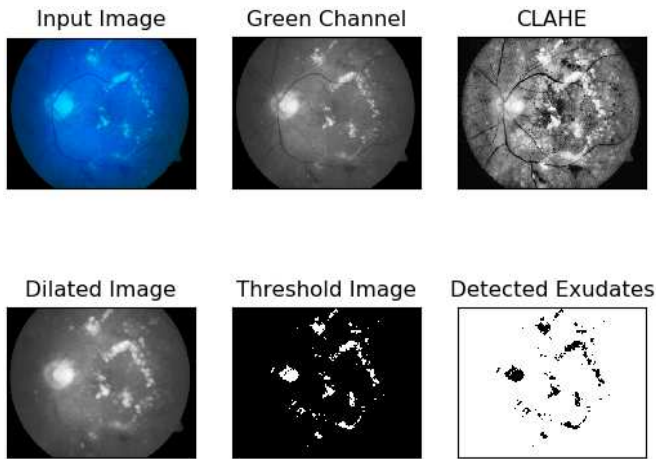


Figure 6: Exudates extraction system

3. Feature Extraction

In summary, we have used nine quantitative features for training and for classification, which are Energy, Contrast, Entropy, Homogeneity, Correlation, Dissimilarity, ASM, Mean and Standard deviation.

A. Testing Phase

Testing phase verifies the different stages of DR. Test retinal fundus image from the dataset is taken as input. The image maybe of format .jpg, .ppm, .bmp, .gif etc.

1. Preprocessing, Detection and Feature Extraction:

Preprocessing steps on test image, Detection of blood vessels and exudates, and feature extraction steps are carried out in the same as explained in the training phase.

2. Classification:

The vector feature array of energy, contrast, entropy, homogeneity, correlation, dissimilarity, asm, mean and standard deviation is used as testing on SVM and KNN classifier.

Support Vector Machine is a supervised machine learning algorithm. SVM offers very high accuracy as compared to other classifiers such as decision trees and logistic regression. It is better known for its kernel trick to handle non-linear input spaces. SVM is widely used for face detection, classification of emails, handwriting recognition, intrusion detection and classification of genes. It uses hyper plane to separate the data points with the largest amount of margin. It finds an optimal hyper plane, which helps in the classification of new data points. SVM gives poor performance if the number of features extracted during the process of the algorithm is much greater than the number of samples present in the dataset. Therefore it is always a better option to have limited number of features for the purpose of classification. Since the data is nonlinear data selection of kernel is needed in SVM.

k-Nearest Neighbors is also a supervised machine learning algorithm. Lazy learners such as nearest neighbor classifiers do not require model building. Nearest neighbors are used to determine the class label of test example. k-nearest of a given example z refer to the k points that are closest to z. If the value of k is too small, then the classifier maybe inclines towards over fitting because of noise in training data. If value of k is large, then the classifier ends up misclassifying the test data because the list of nearest neighbors may consist of

data that maybe located away from its neighborhood. k-NN classifier learns from a labelled training set by taking in the training data X along with its labels y and learns to map the input X to its desired output y, which means the k-NN model learns from the training set and predicts the output class as majority of k-NN.

In this paper, classification is divided into three stages: normal, moderate non-proliferative DR stage and severe non-proliferative DR stage.

V. EXPERIMENTAL RESULTS

A. Performance Evaluation of DR identification system

Performance of Diabetic Retinopathy identification system is usually calculated using Sensitivity, Specificity and Accuracy. To obtain these it is necessary to find evaluation parameters True Positive (TP), False Negative (FN), True Negative (TN) and False Positive (FP). Sensitivity measures the actual positives that are correctly identified which means that the patient has DR. Specificity measures the proportion of negatives that are correctly identified.

Sensitivity is the fraction of positive examples correctly predicted by the model. The sensitivity of the test can be determined by the formula:

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

Specificity is the fraction of negative examples correctly predicted by the model. The specificity and accuracy of the test can be determined by the formula:

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

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

Recall and Precision metrics that are widely used where successful detection of one of the classes is considered more significant than detection of other class. Precision is the fraction of examples that turn out to be positive in-group the classifier has declared as positive class. Higher the precision, lower the number of false positive errors by classifier. Precision can be determined by the formula:

$$\text{Precision, } p = \frac{TP}{TP + FP} \times 100$$

Recall is the fraction of positive examples that are correctly predicted by the classifier. Classifiers with large recall have very few positive example misclassified as negative class. Recall can be determined by the formula:

$$\text{Recall, } r = \frac{TP}{TP + FN} \times 100$$

B. Datasets

Dataset of 20 images from the hospital Goa Lasik MY EYE, Centre for Laser eye surgery & comprehensive eye care services, Goa, and Five publicly available databases: (1) ABNORMAL dataset, (2) DRIVE dataset, (3) Standard Diabetic Retinopathy Database 'Calibration Level 0' (DIARETDB0), and (4) Standard Diabetic Retinopathy Database 'Calibration Level 1' (DIARETDB1) and (5) ALL RETINOPATHY are used. Table I shown below shows the details on the database images used.

Table I Databases

Datasets	Resolution	Healthy images	Diseased images	Total
Hospital	711 x 703	7	13	20
Normal-Abnormal	720 x 560	0	30	30
Drive	565 x 584	33	7	40
Diaretdb1	1500 x 1152	5	74	89
Diaretdb0	1500 x 1152	20	110	130
All Retinopathy	150 x 130	30	15	45
Total		95	250	345

C. Results

The evaluation of our proposal was implemented in Python 3.6. Training of the system was done manually by setting the range of the extracted features for blood vessels and exudates. We have taken total 375 images, out of those 345 images, 295 images were taken for training purpose. From 295 training images, 100 images were normal and 195 images were of DR. The test dataset consisted of 80 images and from 80 images, 25 images were normal and 55 images were of DR. Table II and Table III shows the performance of the classifiers.

From Table II, it is clear that SVM with kernel as rbf achieves the best results. From this table, it can be inferred that all 9 patients were correctly classified negative (TN). True Negative (TN) is the result where cases without the disease is correctly classified as negative. This gives the value of False Positive (FP) as 0 which means cases without the disease is named as positive. When we go for classification of the disease, it is seen 4 patients were classified as negative. This gives us False negative (FN). Finally, 23 patients were classified correctly as positive with disease (True Positive). With the above conclusion it is clear that SVM with rbf kernel achieves the best results.

TABLE II Specificity, Sensitivity, Accuracy, Precision, Recall, F-Measure of Exudates With Different Classifiers

Method	Classifier Name		
	k-NN	SVM with linear kernel	SVM with rbf kernel
TP	21	19	23
TN	8	7	9
FP	1	2	0
FN	6	8	4
Specificity %	88.89	77.78	100
Sensitivity %	77.78	70.3	85.18
Precision %	95.45	90.4	100
Recall %	77.77	70.3	85.18
F-measure %	85.7	79.1	92
Accuracy %	80.56	72.2	85.18

TABLE III Specificity, Sensitivity, Accuracy, Precision, Recall, F-measure of Blood Vessels with different classifiers

Method	Classifier Name		
	k-NN	SVM with linear kernel	SVM with rbf kernel
TP	20	21	20
TN	15	13	16
FP	1	3	0
FN	8	7	8
Specificity %	93.75	81.3	100
Sensitivity %	71.4	75	71.42
Precision %	95.23	87.5	100
Recall %	71.4	75	71.4
F-measure %	81.63	80.76	83.4
Accuracy %	79.5	77.2	81.9

From Table III, we can see SVM with rbf kernel achieves the best results. From this we can see 16 patients were tested negative with the disease. This leads us to True Negative (TN). Similarly, it can be seen the value of False Positive (FP) is 0 which means the cases without the disease is named as positive. Only 8 patients with ailment were ordered as negative. Thus giving value of False Negative (FN) as 8. However, when we come to classify the disease, 20 patients were correctly classified by the classifier giving us value as 20 for True Positive (TP). With the above conclusion we can see SVM with rbf kernel achieves the best results.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a Diabetic Retinopathy Detection System for classification of retinopathy stages from the retinal images. From the results of the proposed detection system from colored fundus images with SVM and k-NN classifiers, it can be concluded that from the pre-processing, feature extraction, SVM and k-NN classifiers to classify the different stages of the disease from the blood vessels and exudates, SVM with rbf as kernel gives best results in the classification of diabetic retinopathy for both exudates and blood vessels. The system can identify different stages of the disease with an average accuracy of more than 85%, a specificity of 100%, a sensitivity of 85.18% for exudates and an average accuracy of more than 81%, a specificity of 100% and a sensitivity of 71.4% for blood vessels.

As an extension to the proposed work, it is suggested to optimize the features selected and the different classifier techniques can be compared and analyzed. In addition to this blood vessels and exudate detection and classification system, inclusion of hemorrhages and microaneurysms can facilitate ophthalmologists to make better conclusions. Also as future works, the detection of soft and hard exudates and applying textural analysis can improve the accuracy of the system. Different filtering techniques can be used in preprocessing for detection and the results can be analyzed and compared. Many more features can be extracted from the attributes like, optic distance, red lesions, renyi's entropy, edema, fovea etc. to classify the disease in multiple classes based on features and their performance can be

evaluated on different measures. As the existing systems are quiet slow in the operation, a real time implementing screening system will provide better performance.

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