FEATURE EXTRACTION TO DETECT AND CLASSIFY DIABETIC RETINOPATHY USING FUNDAL IMAGES

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Abstract— Diabetic retinopathy (DR) is a human eye disease found in diabetics that damages the retina and can lead to long-term vision loss. It causesvisual impairment and, in the worst case, severe blindness as lesions form in the retina due to rupture of retinal vessels. Early detection of the disease has become critical to avoid exacerbation and difficulty in identifying subtle lesions in advanced stages of the disease. The main cause of blindness is believed to be asymptomatic in the early stages. Diagnosis of these diseases is time-consuming and difficult for ophthalmologists. Early detection andclassification of DR cases is an important step in providing needed treatment. This work is mainly focused on DR detection and classification based on features extracted from retinal fundus images. Feature extraction for DR detection and classification includes microaneurysm detection and Exudates detection. The proposed system consists of phases such as Pre-processing which includes image resizing, Green channel separation, and CLAHE (Contrast Limited Adaptive Histogram Equalization), Gray-Level Co-occurrence Matrix (GLCM)-based method is used to extract textural features, i.e., exudates and microaneurysms, from retinal fundus images. Evaluating the results, the proposed method showed better performance on real-time dataset collected from LV Prasad Eye Hospital.

Keywords— **Machine Learning, Diabetic Retinopathy, Image Processing, Microaneurysm detection, Exudates detection**

1. INTRODUCTION

The anatomy of the eye is complicated. The major structures of the eye have associated changes that can affect the eye and surrounding structures. Diabetic retinopathy is the leading cause of blindness in adults from age 20 to age 74 in the United States. Diabetic retinopathy is caused by elevated glucose levels in the optic nerve. High blood sugar can block blood vessels in the optic nerve, causing leakage and swelling. There are several signs to recognize Diabetic Retinopathy, such as micro-aneurysms(MAs), hemorrhages,hard exudates, cotton wool spots, and venous loops. Under certain conditions, the optic nerve of patients with diabetic retinopathy experiences abnormalities as it grows on the surface of the retina. If not detected early, it can lead to blindness. Symptoms in DR patients are difficult to identify and it is too late for effective treatment. Therefore, detection and early medical intervention are critical. Ophthalmologists typically observe DR based on features such as vessel segmentation, hemorrhage, microaneurysms (MA), texture, and vasodilation. MA is the first scientific sign indicating and identifying as red lesions of diabetic retinopathy.

The basic method of diagnosis is for a doctor to examine a person's eyes and perform tests to determine what disease the personhas. Detecting and classifying diabetic retinopathy is a time-consuming process, and time is of the essence when cases are severe. Therefore, an automated system is required to do the job correctly and efficiently. Early diagnosis and continuous monitoring of patientssuffering from ocular diseases have been major concerns in computer-aided detection techniques.

Texture features have properties that describe visual patterns based on the spatial definition of an image. Identifying a particular texture in an image is done by representing the texture as a two-dimensional Gray-level variation known as a Gray-level co-occurrence matrix (GLCM). GLCM is defined as a statistical method for finding textures that considers spatial relationships of pixels. The GLCM function computes the frequency of occurrence of pixel pairs with a particular value and a particular pixel relationship in the image, and subsequently extracts a statistical measure from a matrix defining normalized probabilities of the co- occurrence matrix to determinethe texture of the image.

Automatic detection of eye diseases by analyzing retinal images provides a better alternative for timely diagnosis and treatment of eye diseases. This allows patients to consult an ophthalmologist in terms of screening. This proposed system consists of three majorsteps, at first the retinal image is taken as input, Then the GLCM features are extracted from the image as second step. Then the third step involves classifying the Diabetic Retinopathy into different classes. The developed model is less complicated with a good accuracy.The following Fig. 1 and Fig. 2 shows the retinal images of DR and No DR.

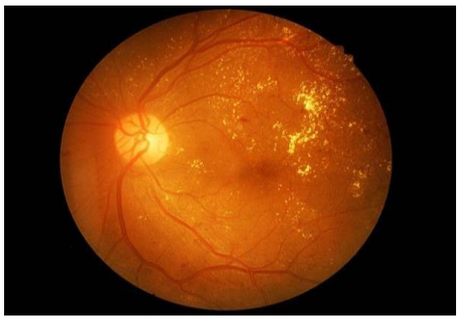

Fig. 1 Image affected with Diabetic Retinopathy

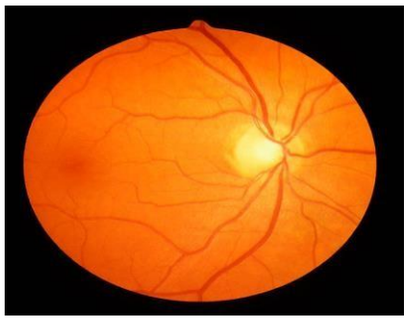

Fig. 2 Normal Retinal mage

2. LITERATURE SURVEY

[Helena M. Pakter and et.al 2011] suggested a computer-assisted method of retinal vessel analysis by a micro densitometry method ofcolor retinography was able to precisely measure the complete blood column that fills the vessel lumen, including the central red bloodcells and the peripheral plasma stream. Studies of correlations between vessel diameters and cardiovascular outcomes should therefore assume that micro densitometry methods of color FPs measure only the complete vessel lumen. Pearson correlation coefficients and Bland-Altman plots were used to evaluate the agreement between the measurements made by FP and FA.It is not clear which component of the vessels they are measuring [1].

[R. Priya and P. Aruna 2013] developed a system used pre-processing techniques like Grayscale conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, Matched filter Response and Fuzzy C-means segmentation are applied. From the pre- processed images, features were extracted for the classification process. As an achievement of this work, the DR has been classified into two categories NPDR and PDR using PNN, Bayes theory and SVM. All the three techniques used for the classification were goodin performance, but SVM is more efficient than PNN and Bayes Theory from the obtained results. Thus this work has given a successful Diabetic Retinopathy Diagnosing method which helps to diagnose the disease in early stage which mutually reduces the manual work.PNN has achieved an accuracy of 87.69% Bayes Classifier has an accuracy of 90.76% and SVM has an accuracy of 95.38% [2].

[Muhammad Moazam Fraz, and et.al 2010] proposed an An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation. In this paper, they have presented an effective retinal vessel segmentation technique based on supervised classification using an ensemble classifier of boosted and bagged decision trees. They have used a 9-D feature vector which consists of the vessel map obtained from the orientation analysis of the gradient vector field, the morphological transformation; line strength measures and the Gabor filter response which encodes information to successfully handle both normal and pathological retinas. The ensemble classifier was constructed by using 200 weak learners and is trained on 20 0000 training samples randomly extracted from the training set of the DRIVE and 75000 samples from STARE databases. Their algorithm achieved best accuracy in the case of the cross-trained classifier for DRIVE and STARE; the cross-trained accuracy of Marin is slightly better. In addition, the simplicity of the method should also be high-lighted. The algorithm is a suitable tool for automated retinal image analysis [3].

[S. Muthu Lakshmi et. al 2010] suggested a Supervised Blood Vessel Segmentation in Retinal Images Using Feature Based Classification. This paper proposes a supervised method for blood vessel detection based on feature classification. The required feature vector is calculated from the preprocessed retinal images in the neighbourhood of the pixel under consideration. The following processstages may be identified: 1. Selecting the input image from the database, 2. Fundus image preprocessing for Gray-level homogenization and blood vessel enhancement, 3. Feature extraction for pixel numerical representation, 4. Post processing for removing the falsely detected isolated pixels. The input images are read from the DRIVE database. The green channel provides the best vessel-background contrast of the RGB representation. This method of blood vessel detection uses feature based pixel classification. Membership value ofthese feature based image is also used to segment the blood vessel but The results obtained for region growing algorithm are not completely satisfactory [4].

[P. C. Siddalingaswamy, and et.al 2010] proposed an Automatic detection of multiple oriented blood vessels in retinal images Automatic segmentation of the vasculature in retinal images is important in the detection of diabetic retinopathy that affects the morphology of the blood vessel tree. In this paper, a hybrid method for efficient segmentation of multiple oriented blood vessels in colour retinal images is proposed. Initially, the appearance of the blood vessel s is enhanced and back-ground noise is suppressed withthe set of real component of a complex Gabor filters. Then the vessel pixels are detected in the vessel enhanced image using entropic thresholding based on Gray level co-occurrence matrix as it takes into account the spatial distribution of Gray levels and preserving the spatial structures. The performance of the method is illustrated on two sets of retinal images from publicly available DRIVE (Digital Retinal Images for Vessel Extraction) and Hoover's databases. For DRIVE database, the

blood vessels are detected with sensitivity of86.47±3.6 (Mean±SD) and specificity of 96±1.01. These images are of very large variability in terms of fundus disease and image quality and were used to test the robustness of proposed retinal vessel detection method but These methods suffer from problems associated with detecting smaller and tortuous vessels that are prone to changes in background intensity [5].

[Ana Maria Mendonça, and et.al 2007] proposed an algorithm for the automated detection of the retinal vascular network which combines differential filters, for centerline extraction, with morphological operators, used for filling vessel segments. Several intensityand morphological properties of vascular structures, such as linearity, connectivity, and width, are considered in the approach. The segmentation of blood vessels here in described has the following main phases: 1) image preprocessing for background normalization and thin vessel enhancement; 2) vessel centerline detection for defining a set of points in the central part of the vessels; 3) seeded region growing, to fill finally the blood vessels. Vessel centerlines, considered as local intensity maxima along vessel cross profiles, are detected using the signs of four directional operators. These centerline segments are the seeds for an iterative region growing process, which in each step uses one level of a multiscale representation of the vascular structure based on a morphological approach with variable sized structuring elements. The method was evaluated using the images of two publicly available databases, the DRIVE database and the STARE database.This algorithm outperforms other solutions and approximates the average accuracy of a human observer without a significant degradation of sensitivity and specificity.It has not yet been extensively explored[6].

[Jingdan Zhang Yingjie Cui, and et.al 2015] proposed Blood Vessel Segmentation of Retinal Images Based on Neural Network**.** This study proposes a retinal vessel segmentation method based on neural network algorithm. To overcome the problem of low contrast andlarge variability in retinal images, and construct the feature vector with the intensity from green channel and the vessel enhanced intensity feature. Then, classify the pixels in retinal image with SOM algorithm. Finally, label each neuron in the output layer of SOM.as retinal neuron or non-vessel neuron with Otsu's method, and get the final segmentation results. The method is validated on the DRIVE database with available gold standard images. From the visual inspection and quantitative validation of the method in the experiments, it is evident that the proposed method is robust to the low contrast and large variability in the retinal images, and gets accurate segmentation results. [7].

[Benson S. Y. Lam, and et.al 2010] suggested a General Retinal Vessel Segmentation Using Regularization - based Multi - concavity modeling. This paper presents a novel regularization -based multi -concavity approach for effectively segmenting blood vessels in both normal and pathological retinas with bright and dark lesions in a single system. A perceptive transform derived from Weber's law is proposed to map an input image into a perceptive space for robust vessel segmentation. The results showed that system performances of both accuracy and R area tested on grey -scale intensity, RGB and L*a*b* color channels are consistently better in the perceptive space than in the image space, demonstrating the broader effectiveness of the proposed perceptive space method. As the bright lesion has a steep intensity transition profile, measuring the degree of concavity can effectively distinguish the bright lesions from the vessels and non -vessels. The proposed method shows very attractive performances not only on healthy retinas but also on a mixture of healthyand pathological retinas [8].

[Razieh Akhavan, and et.al 2010] proposed A Novel Retinal Blood Vessel Segmentation Algorithm using Fuzzy segmentation. This technique is based on vessel centerline detection and fuzzy segmentation. The proposed vessel extraction technique has consistent performance in both normal and abnormal images. To validate the proposed method, they used images provided from two public databases, DRIVE and STARE databases. They could achieve the greatest specificity, accuracy and sensitivity, 95.13%, 72.52% and 97.33% for the DRIVE database and 95.37%, 77.66% and 96.80% for the STARE database. This algorithm is very effective method todetect retinal blood vessels [9].

[Attila Budai, and et.al 2010] proposed Multiscale Blood Vessel Segmentation in Retinal Fundus Images. The proposed algorithm startswith the extraction of blood vessel centerline pixels. The final segmentation is obtained using an iterative region growing method that merges the binary images resulting from centerline detection part with the image resulting from fuzzy vessel segmentation part. In thisproposed algorithm, the blood vessel is enhanced using modified morphological operations and the salt and pepper noises are removedfrom retinal images using Adaptive Fuzzy Switching Median filter. This method is applied on two publicly available databases, the DRIVE and the STARE and the experimental results obtained by using green channel images have been presented and compared withrecently published methods. The results demonstrate that the algorithm is very effective method to detect retinal blood vessels.

Most of the existing algorithms used DRIVE and STARE databases, and majorly concentrated on Blood Vessels segmentation [10].

Our proposed system uses a real time dataset labelled by an expert ophthalmologists and focused on extracting the features Micro- aneurysms detection, and Exudates detection for detecting and SVM algorithm is used for classifying DR into different classes.

3. DATASET

Real-time dataset is collected for classification to overcome all shortcomings of existing systems. In existing systems, the images used are already processed at high resolution. However, in real time, images can have various resolution issues, noise, and image sharpness issues. Here for this work the retinal fundus images are collected from the L V Prasad eye institution. It consists of 250 fundus images of diabetic retinopathy. Fundus images are captured by various cameras in the market, such as Canon, Zeiss, and Kowa, resultingin varied image resolutions. Annotations were labelled by trained human expert.

The dataset includes images belonging to 5 different classes.

- MILD DR consists 50 images
- SEVERE DR consists 50 images
- MODERATE DR consists 50 images
- PDR consists of 50 images
- NON-DR consists of 50 images

4. METHODOLOGY

A. Architecture of the System

The proposed image processing model for DR detection and classification is mainly used to analyze the blood vessel of the retinal fundus image for the features exudates, microaneurysms. Exudate is a lipid and lipoprotein deposit that occurs near leaky capillaries inthe retina. In the first stage of DR, the retinal image contains many small red spots 10–100 μm in diameter. These tiny red spots are called microaneurysms. The retinal fundus images may be subjected to noise, 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 pre-processing 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. Thresholding segmentation is applied to extract foreground of the image. Gray Level Co-occurrence Matrix (GLCM) algorithm is usedto get the features of segmented images such as Energy, Entropy, Homogenity, Contrast, Correlation. Over the extracted GLCM features, Support Vector Machine, a machine learning technique is applied to classify the image into different classes. This research represents a possible improvement in the detection and classification of diabetic retinopathy over real time images and finally the performance of proposed model is calculated using accuracy, precision, and recall.

The architecture of the model Fig. 3 shows the entire process.

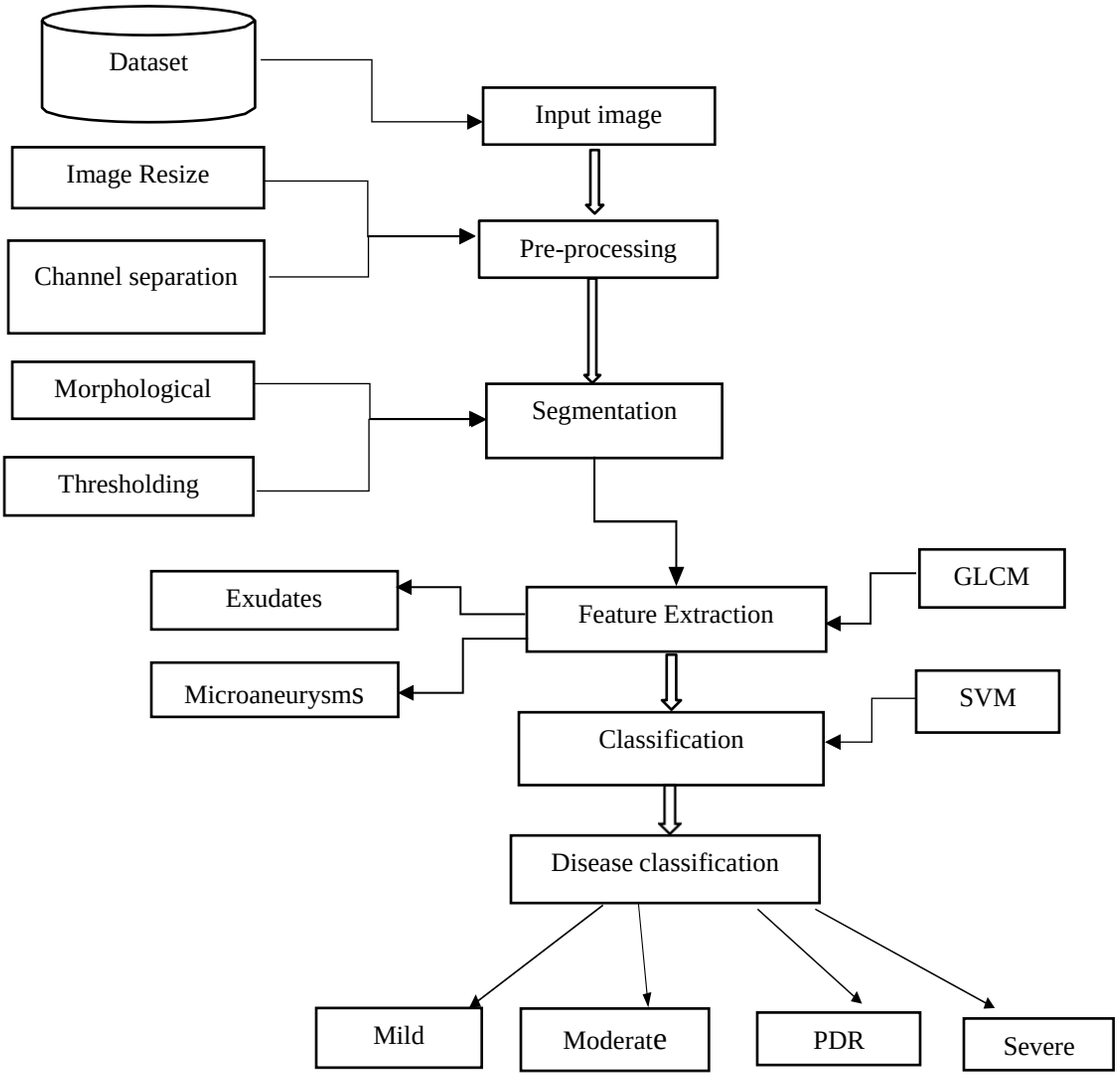

Fig. 3 Architecture of the proposed system

The modules in the proposed model are:

i) Pre-processing of Data

In the first stage, the collected input images undergo preprocessing. This involves resizing the image to 256 x 256 and extracting the green channel of the image. To reduce image variability and improve image quality, a median filter is applied to the greenplane image to reduce noise before (CLAHE) contrast-limited adaptive histogram equalization is applied. Median filtering is a nonlinearmethod used to reduce noise. CLAHE algorithm is applied to improve the contrast of the image which helps in better feature extraction.

ii) Segmentation

Image segmentation aims to subdivide and group similar regions or segments of an image under their respective class designation. Thisstep converts the green channel image to a Grayscale binary image. The simplest method of segmentation in image processing is the threshold method. Subdivide the pixels in the image by comparing the pixel intensity to a certain value (80). Since the retinal image hasa higher intensity than the background, using a threshold for segmentation purposes is very appropriate.

iii)Feature Extraction

In this step, the GLCM algorithm is used to extract the textural features from the images and those extracted features will be saved as the train and test features.

Calculate the selected Feature. This calculation uses only the values in the GLCM. Let(x, y) represent images of size $Nx$and Ny that have pixels with L levels and r is the direction vector of spatial offset. $(i,)$ is a GLCM function and defined by the number of pixels (j)occurring at offset r to pixel $(i)$and where the offset r can be an angle or distance, $i\in$ 1,2, . . , L and $j\in$ 1,2, . . , L.

GLCM function can be seen in equation $(i,) = \{(x1 , y1), (x2 , y2)\}$. (1)

1. ***Contrast:*** Contrast is the ratio of the brightness intensity between pixel of that image. That result of the image is good if thathave a high brightness intensity. Contrast can be obtained with equation .

$Contrast = \sum\sum|i - j|\ 2(i,)\ LjLi$, (2) where $p(i,j)$ is matrics co-occurrence, $i\in$ 1,2, . . , L and $j\in$ 1,2, . . , L.

2. ***Homogeneity***: Homogeneity is a value from the level of uniformity at the local Gray level. Homogeneity is can be called Inverse Difference Moment (IDM). Homogeneity is inversely proportional to the value of contrast and high contrast value have low homogeneity). The homogeneity equation can be seen in equation.

$Homogeneity = \sum\sum\ (i,)\ 2\ 1 + (i - j)\ 2\ Lj{=}1\ Li{=}1$.

3. ***Entropy:*** Entropy can be used to search for information on images and the results obtained based on the amount of missing information present in the image The entropy equation can be seen in equation.

$Entropy = \sum\sum(i,j)(-\ln p(i,j))\ Lj{=}1\ Li{=}1$

4. ***Energy:*** Energy is the uniformity of co-occurrence matrix. This energy can also be called Angular Second Moment. The energy equation can be seen in equation.

$Energy = \sum\sum\ (i,)\ L\ 2\ j{=}1\ Li{=}1$.

5. ***Correlation:*** Correlations are used to measure the degree of interconnectedness or dependency between pixels and other pixels

. The correlation equation can be seen in equation.

$Correlation = \sum\sum\ (i - \ )(j - \mu j)p(i,j)\ \sigma i\sigma jLj{=}1\ Li{=}1$,where $\mu i = \sum i\sum p(i,j)\ ij$

$\mu j = \sum j\sum p(i,j)\ ji$

$\sigma i = \sum(i - \mu i\ )\ 2\sum p(i,j)\ ij$

$\sigma j = \sum(j - \mu j\ )\ 2\sum p(i,j)\ ji$

v) Classification

This step uses an SVM classifier to classify the input as mild, severe ,moderate , PDR and No DR images. The Support Vector Machineis used for classification, because it is suitable for smaller datasets and also gives greater accuracy, it works really well with a clear margin of separation, and it is effective in high dimensional spaces. Based on the features extracted from the retinal image, it will be concluded that whether the given retinal image is effected with diabetic retinopathy or not and each image in the frame is further classified as abnormal (PDR, MILD, MODERATE, SEVERE) or normal (normal retinal image).

vi) Performance Estimation

- True positive (TP) = the number of cases correctly identified as patient.
- False positive (FP) = the number of cases incorrectly identified as patient.
- True negative (TN) = the number of cases correctly identified as healthy.
- False negative (FN) = the number of cases incorrectly identified as healthy.

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = (TP+TN) / (TP+TN+FP+FN);

Precision: The Precision evaluates the fraction of rightly classified instances or samples among the ones classified as positives.Therefore, the formula of the precision can be mathematically written as,

Precision = TP / (TP + FP)

Recall: The Recall is the ability of a model to find all the relevant cases within a data set. Mathematically, we define recall as the number of true positives divided by the number of true positives plus the number of false negatives written as,

Recall=TP/(TP+FN).

5. Results and Discussions

In order to show the generalization ability of the proposed system, we evaluated the performance of the proposed system using the fundus images dataset that is provided by LVPEI hospital, which consists of several diabetic retinopathies affected retinal images about of 250 images, that is adequate for the GLCM based model. The feature extraction starts from an initial set of measured data and buildsderived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. The Categorical classifier is trained using features extracted from the retinalimages data training set and tested on one-fourth of the retinal images dataset. A simple function is created, it takes the filename of theimage (along with path) as input and load it using load image method of image scaling and resize the image as 250X250 with the helpof matplot lib plot it , convert it into a raster graphics image with no loss of quality , a new image with a higher or lower number of pixels must be generated, which we pass as an input to predict method of the model object. The segmented regions are considered for the prediction of diabetic retinopathy feature extraction and classification of the image, considering the GLCM features values that arestored in pickle file.

Type of DR	No. of Images
PDR	50
MILD	50
SEVERE	50
NORMAL	50
MODERATE	50

Table 1: Total number of images : 250

The data is divided into train data and validation data. The training data consists of 195 images of each disease including normal. Thetesting data consists of 55 images of each disease including normal.

The Screen shots of the results are shown below

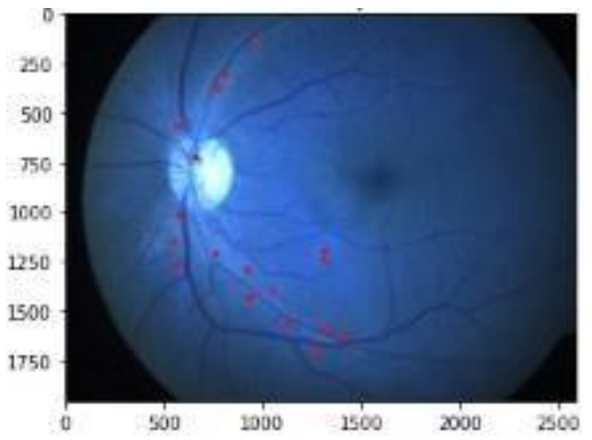

Fig. 4: Microaneurysms extraction

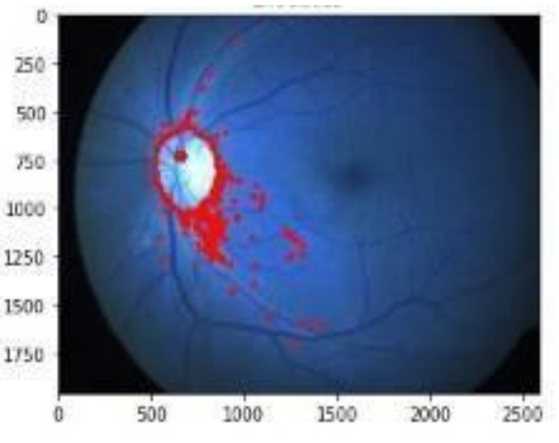

Fig.5 Exudates extraction

```
 GLCM FEATURE
**********************************
----------------------------------
[6.3061224489795915, 7.625850340136054, 68.29705215419501, 83.99092970521542]
----------------------------------

SVM Predicted Class: 2
**********************************
-- DR Image Mild --
**********************************
[[15  8  6 21]
 [ 6 31  2 11]
 [12 11 10 17]
 [11 13  2 24]]
```

Fig.6 DR image classified as Mild DR

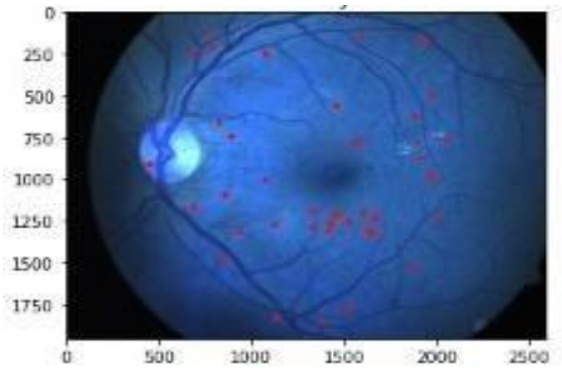

Fig.7 Microaneurysms extraction

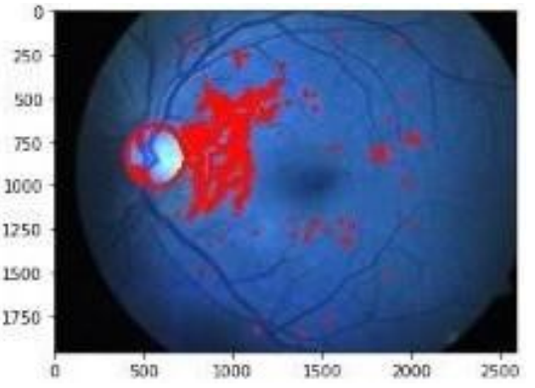

Fig. 8 Exudates extraction

```
**********************************
 GLCM FEATURE
**********************************
----------------------------------
[7.303854875283447, 8.043083900226758, 50.88662131519274, 62.666666666666664]
----------------------------------

SVM Predicted Class: 4
**********************************
-- DR IMAGE Moderate --
**********************************
[[15  8  6 21]
 [ 6 31  2 11]
 [12 11 10 17]
 [11 13  2 24]]
```

Fig.9 DR image classified as Moderate

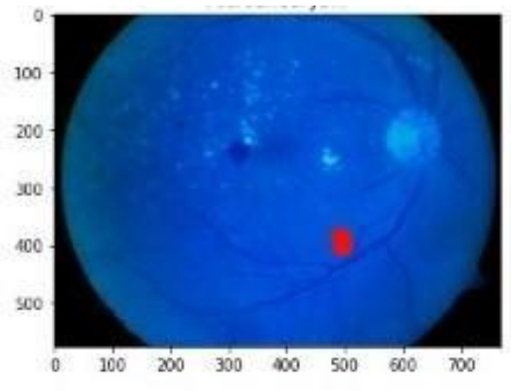

Fig .10 Microaneurysms extraction

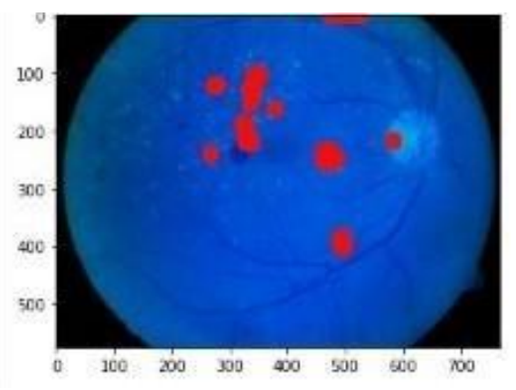

Fig. 11 Exudates extraction

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**********************************
 GLCM FEATURE
**********************************
----------------------------------
[1.4761904761904763, 3.054421768707483, 91.54421768707483, 103.47165532879819]
----------------------------------

SVM Predicted Class: 2
**********************************
-- DR IMAGE PDR --
**********************************
[[15  8  6 21]
 [ 6 31  2 11]
 [12 11 10 17]
 [11 13  2 24]]
======================================
```

Fig.12. DR image predicted as PDR

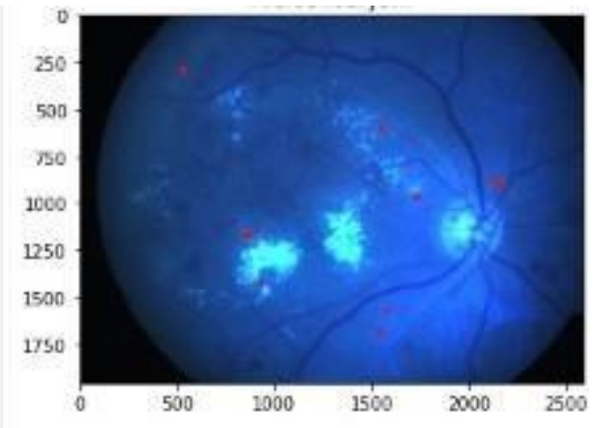

Fig.13 Microaneurysms extraction

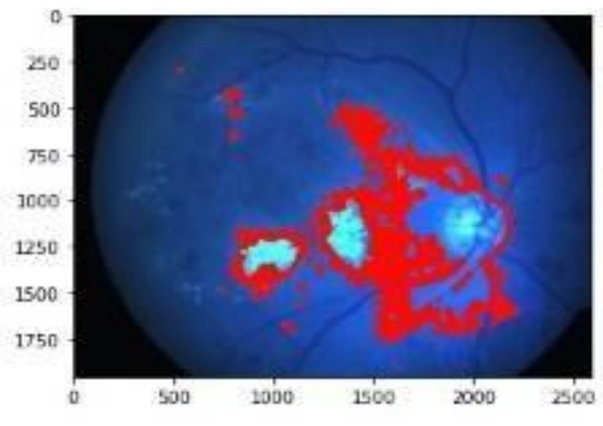

Fig.14 Exudates extraction

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**********************************
 GLCM FEATURE
**********************************
----------------------------------
[4.90702947845805, 5.374149659863946, 60.40816326530612, 72.0702947845805]
----------------------------------

SVM Predicted Class: 4
**********************************
-- DR IMAGE Severe --
**********************************
[[15  8  6 21]
 [ 6 31  2 11]
 [12 11 10 17]
 [11 13  2 24]]
====================================
```

Fig. 15 DR image predicted as Severe

Analysis of Results

The results of the model are measured using performance metrics such as accuracy, precision and recall. The accuracy, precision and recall measures remains constant over the 250 images.

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1) Accuracy  = 76.66666666666667  %
2) Precision = 65.21739130434783  %
3) Recall    = 71.42857142857143  %

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Fig.16 Performance of the classifier

The Accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we shouldcalculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = (True Positives + True Negatives)/ (True positives +True Negatives + False Positives + False Negatives)The model gave us an overall accuracy of 76.67%, precision value of 65.21%, and Recall value of 71.43%.

6. Conclusions

We proposed a GLCM based feature extraction model for extracting features of retinal images to detect Diabetic Retinopathydisease. The proposed method has several unique characteristics. First, our retinal fundus images go through

pre-processing and segmentation. Then GLCM features are extracted using that segmented images. All the retinal fundus images are tested against the trained feature images and detects whether the fundus image is suffering with DR or not. An image with DR is further classified into PDR, MILD, MODERATE and SEVERE. Finally, our method was shown to better handle the challenges in retinal vessel segmentation.

The classification is performed based upon values of microaneurysms area, exudates area marked through GLCM features values. The proposed method achieves 76.67% Accuracy,65.2% Precision, and 71.43% Recall for all the 200 images. This accuracy can be further improved by collecting more real time images or by enhancing Image dataset using augmentation techniques.

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