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Diabetic Retinopathy Detection and Grading Using Machine Learning

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ABSTRACT

Diabetic Retinopathy (DR) is a constantly deteriorating disease, being one of the leading causes of vision impairment and blindness. Subtle distinction among different grades and existence of many significant small features make the task of recognition very challenging. In addition, the present approach of retinopathy detection is a very laborious and time-intensive task, which heavily relies on the skill of a physician. Automated detection of diabetic retinopathy is essential to tackle these problems. Early-stage detection of diabetic retinopathy is also very important for diagnosis, which can prevent blindness with proper treatment. In this paper, we developed a novel system which performs the early-stage detection by identifying all microaneurysms (MAs), the first signs of DR, along with correctly assigning labels to retinal fundus images which are graded into five categories. We have tested our system on the largest publicly available IDRiD diabetic retinopathy dataset, and achieved 77.85% accuracy with Gabor features and Naïve Bayes Classification.

Key words: Diabetic Retinopathy, Gabor features. Naïve Bayes

1. INTRODUCTION

The purpose of this paper is to directly compare the methods developed for automatic image grading of Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME). One of the common diseases all over the world is diabetes in which the lack of insulin causes high blood sugar in humans. Long-term diabetes also affects the human retina resulting in a condition known as diabetic retinopathy (DR). This condition damages the retinal blood vessels causing them to leak which ultimately leads to blindness. The patients of different types of diabetes develop some form of retinopathy after 20 years of this chronic disease. DR of any stage develops in nearly all of the patients having diabetes of type 1 and about 60%of the patients with diabetes of type 2 [1]. The percentage of diabetes patients is high in almost every region of the world especially in industrialized countries which makes a high chance of DR sufferers.

There are several stages of DR such as non proliferative DR (NPDR), proliferative DR (PDR) and maculopathy or macular edema (ME). NPDR is known as background DR, whereas PDR and ME are the advance stages of DR [1].

Diabetic patient can have different signs of retinopathy such as microaneurysms, hard exudates, hemorrhage and cotton wool spots (CWS) at different stages of DR. Microaneurysms are weak dark red spots developed on blood vessels that bulge outward. They are the first detectable change in the retina due to diabetic retinopathy. Hemorrhage is usually round or oval in shape and formed by the rupture of micro aneurysms. They are also dark red in colour and can be located within the mid-retina. Hard exudates and CWS are collectively known as exudates. Hard exudates are yellowish deposits of protein present in the retina. CWS are the soft exudates which are white and fluffy lesions. Diabetic maculopathy or ME is a condition in which the macula is surrounded by the exudates and a patient's central vision is affected. Figure 1 shows the main component of human retina and also the exudates present on the surface of the retina.

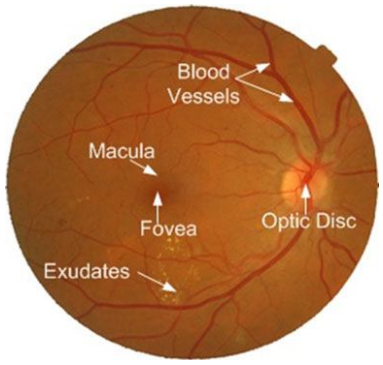

Figure 1: Main components of the human retina along with exudates

Diabetic maculopathy occurs if exudates appear on or near the macula affecting central vision. The central portion of the retina which is usually darkest and rich in cones is called the macula (Fig. 1). The macula is accountable for the clear, sharp and detailed vision [1]. The center of the macula is called fovea which is responsible for very fine details in the image (Fig. 1). The significance of detecting the macula is that it is used for the early detection of various diseases. ME is one of the common sight-threatening conditions among diabetic patients in which the fluid rich in fat leaks out of damaged blood vessels and gets deposited near the macula

and leads to distorted central vision. The human visual loss can be prevented by early screening and diagnosis of diabetic maculopathy. The two types of macular edema are non-clinically significant macular edema (non- CSME) and clinically significant macular edema (CSME). Non-CSME is a mild form of maculopathy in which there are no symptoms of the disease because the locations of exudates are at a distance from the fovea and the central vision is not affected. CSME is the severe form of maculopathy in which the exudates leak out and get deposited very close to or on the fovea affecting central vision of the eye [2]. Irrespective of diabetic retinopathy, long-term diabetic patients have chances of developing diabetic maculopathy.

Diabetic Retinopathy comprises of certain stages which help us to distinguish the severity of the disease and accordingly come up with the prevention methods. The stages of diabetic retinopathy include:

1. No DR: In this stage the eye is not affected with the disease. i.e eye is healthy
2. Mild DR: In the first stage, mild nonproliferative, there will be balloon-like swelling in small areas of the blood vessels in the retina.
3. Moderate DR: In the second stage, known as moderate nonproliferative retinopathy, some of the blood vessels in the retina will become blocked.
4. Severe DR: The third stage, severe nonproliferative retinopathy brings with it more blocked blood vessels, which leads to areas of the retina no longer receiving adequate blood flow. Without proper blood flow, the retina can't grow new blood vessels to replace the damaged ones.
5. Proliferative DR: The fourth and final stage is known as proliferative retinopathy. This is the advanced stage of the disease. Additional new blood vessels will begin to grow in the retina, but they will be fragile and abnormal. Because of this, they can leak blood which will lead to vision loss and possibly blindness

In this paper we present a method for diabetic retinopathy detection and grading. This method is divided into two stages: features extraction and classification/Grading. In the first one, we have used Gabor, LBP and statistical features to extract local features, while in the second stage, we have evaluated the performance of diabetic detection and grading using different machine learning algorithms including SVM, KNN, Naïve Bayes, Neural networks and Decision Trees. Preliminary results show that Naïve Bayes classification with Gabor features gives more promising results.

This paper consists of five sections. "Related Work" section explains the related work with respect to diabetic maculopathy. The proposed system and its complete explanation are given in the "Proposed Methodology" section. The "Experimental Results" section represents the standard retinal image databases which we have used to evaluate the proposed system. The experimental and comparative results of the proposed system using different evaluation parameters and databases are also elaborated in this section followed by discussion and conclusion in the last section.

2. RELATED WORK

The main difficulty faced by DR affected patients is that they are unaware of the disease until the changes in the retina have progressed to a level that treatment will in turn tend to be less effective. Automated screening techniques for the detection purpose have great significance in saving cost, time and labour. The screening of diabetic patients for the development of diabetic retinopathy can reduce the risk of blindness by 50%.With the increase in the rate of the patients affected by the disease there is all the more need for automated systems to take the charge since the number of ophthalmologists is also not sufficient to cope with all patients, especially in rural areas or if the workload of local ophthalmologists is substantial. Therefore, automated early detection could limit the severity of the disease and assist ophthalmologists in investigating and treating the disease more efficiently. There may exist different kind of abnormal lesions caused by diabetic retinopathy the most frequent being exudates, hemorrhage, microaneurysm. A handful of researches have been presented in the literature for Diabetic Retinopathy using various methods. Recently, the use of automation method using fundus images for DR have received a great deal of attention among researchers. A brief review of some recent researches is presented here.

Although extracting vessels before detecting DR with machine learning can achieve high accuracy, it is time-consuming to create the marked ground-truth for retinal vessels. Another paradigm is to train the computer to automatically learn how to distinguish levels of DR by reading retinal images directly, without performing vessel segmentation. In 2000, Ege et al. [3] proposed an automatic analysis of DR by different statistical classifiers, including Bayesian, Mahalanobis, and k-nearest neighbor. Silberman et al. [4] introduced an automatic detection system for DR and reported an equal error rate of 87%. Karegowda et al. [5] tried to detect exudates in retinal images using back-propagation neural networks (BPN). Their features were decided by two methods: decision trees and genetic algorithms with correlation-based feature selection (GA-CFS). In their experiment, the best BPN performance showed 98.45% accuracy. Kavitha and Duraiswamy [6] did some research on automatic detection of hard and soft exudates in fundus images, using color histogram thresholding to classify exudates. Their experiments showed 99.07% accuracy, 89% sensitivity, and 99% specificity. In 2014, de la Calleja et al. [7] used local binary patterns (LBP) to extract local features and artificial neural networks, random forest (RF), and support vector machines (SVM) for detection. In using a dataset containing 71 images, their best result achieved 97.46% accuracy with RF.

Recently, automated systems for detecting diabetic retinopathy stages have widely explored and gained a lot of acceptances [8,9,10,11,12,13,14]. Azzopardi et. al [15] proposed a blood vessels detection method based on Bar-Combination of Shifted Filter Responses BCOSFIRE approach. Prasad et.al [16] proposed a method to detect blood vessels, exudates and microaneurysms using Haar Wavelet transform and Principal Component Analysis techniques. Enrique V.Carrera [17] proposed a computer assisted diagnosis based on the digital processing of retinal images to automatically classify the grade of non-proliferative diabetic retinopathy at any retinal image. These

methods are performed in two steps, first detecting the amount of bleeding and permeate and then giving the results of the lesion after synthesis. The method proposed in this paper input the images, it automatically performs feature extraction and feature processing to directly obtain the classification result. The processing is simpler and the recognition effect is similar. In this paper, we proposed a diabetic retinopathy detection method based on deep learning. Through experiments, the effectiveness of multi-self-attention network model for feature extraction and classification is proved.

3. METHODOLOGY

Diabetic retinopathy is a complication of diabetes. In long-term high glucose environment, retinal vessels will produce a series of pathological changes, such as micro aneurysms, hard exudate and soft exudate. According to the severity of lesions, DR can be divided into No DR, Mild DR, Moderate DR, Severe DR, Proliferative DR in five stages [8]. About 50% patients with diabetes have some stages of the disease, resulting in visual impairment or blindness. How to distinguish between these stages accurately is a complex problem to be solved urgently. Diabetes mainly affects the entire retina by affecting the blood vessels in the retina. According to the changes in various characteristics of the blood vessels in the lesion image, the texture features of the retinal image and the color characteristics of the retinal image are taken as the main features of the detection of diabetic retinopathy.

The proposed methodology for detection and grading of Diabetic Retinopathy is divided into following stages:

1. Preprocessing
2. Optic Disc Removal
3. Blood Vessel Segmentation and Removal
4. Compute the area of Microanesyms and Haemorhages
5. Features Extraction
6. Classification/Grading

3.1 Preprocessing

Biomarkers above are dependent on the quality of images taken from different modalities. A lot of work has been done by researchers since the last two decades to enhance the images quality so that the ophthalmologists can quickly determine abnormalities from them. The performance of DR detection techniques depends on image processing algorithms like enhancement and segmentation of images to extract useful information. These techniques are also utilized to enhance the visuals of images. Also, it is essential to improve low contrast data of retina blood vessels with respect to the background. Otherwise, it 's hard to extract the abnormalities. Some enhancement methods were used such as histogram equalization and other enhancement techniques to improve the contrast of images. Contrast stretching is one of the essential image enhancement techniques.

In the proposed system, CLAHE is utilized for local and global enhancement. CLAHE is a small window built method which is utilized to improve the distinction of retinal blood vessels with reference to its background keeping the bright and dark areas in perspective. It further improves the vessels in changing environment uniformly, and it is an extended technique of histogram equalization and contrast stretching. The main reason of utilizing CLAHE is to apply it on small tiles obtained by dividing the image into small window's image. Grey level values are uniformly dispersed earlier inside the window to confirm an observable concealed structure. Mean filter using CLAHE is used to improve the fundus image. This identifies the vessel. Later, bottom-hat morphological transformation is applied to eliminate the retinal vasculature. Background noise elimination is done through contrast stretching to decrease surplus line structures

3.2 Optic Disc Removal Using Morphological Operations

Different morphological operations used for optic disc removal are as below:

1. `se = strel('disk' ,8);`
   SE = strel(shape, parameters) creates a structuring element, SE, of the type specified by shape. This table lists all the supported shapes.
2. IM2 = imclose(IM,SE) performs morphological closing on the grayscale or binary image IM, returning the closed image, IM2. The structuring element, SE, must be a single structuring element object, as opposed to an array of objects. The morphological close operation is a dilation followed by an erosion, using the same structuring element for both operations.
3. IM = imreconstruct(marker,mask) performs morphological reconstruction of the image marker under the image mask. marker and mask can be two intensity images or two binary images with the same size. The returned image IM is an intensity or binary image, respectively. marker must be the same size as mask, and its elements must be less than or equal to the corresponding elements of mask. If values in marker are greater than corresponding elements in mask, imreconstruct clips the values to the mask level.
4. level = graythresh(I) computes a global threshold (level) that can be used to convert an intensity image to a binary image with im2bw. level is a normalized intensity value that lies in the range [0, 1].
5. IM2 = imopen(IM,SE) performs morphological opening on the grayscale or binary image IM with the structuring element SE. The argument SE must be a single structuring element object, as opposed to an array of objects. The morphological open operation is an erosion followed by a dilation, using the same structuring element for both operations.
6. CC = bwconncomp(BW) returns the connected components CC found in BW. The binary image BW can have any dimension. CC is a structure with four fields.
   - Connectivity Connectivity of the connected components (objects)
   - ImageSize Size of BW

- NumObjects Number of connected components (objects) in BW
- PixelIdxList 1-by-NumObjects cell array where the kth element in the cell array is a vector containing the linear indices of the pixels in the kth object.

7. IM2 = imerode(IM,SE) erodes the grayscale, binary, or packed binary image IM, returning the eroded image IM2. The argument SE is a structuring element object or array of structuring element objects returned by the strel function
8. IM2 = imdilate(IM,SE) dilates the grayscale, binary, or packed binary image IM, returning the dilated image, IM2. The argument SE is a structuring element object, or array of structuring element objects, returned by the strel function.
   If IM is logical and the structuring element is flat, imdilate performs binary dilation; otherwise, it performs grayscale dilation. If SE is an array of structuring element objects, imdilate performs multiple dilations of the input image, using each structuring element in SE in succession
   Figure 2 shows the sample retina image used for optic disc removal.

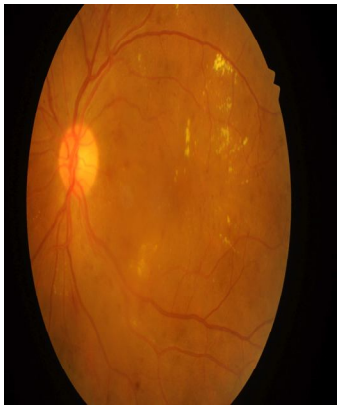

Figure 2: Test Image for Optic Disc Removal
Figure 3 shows the resultant image obtained after optic disc removal.

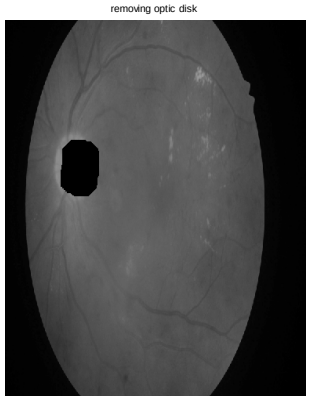

Figure 3: Optic Disc Removal

3.3 Blood Vessel Segmentation and Removal Using Kirsch's Template

Edge detection is a process of distinguishing the pixel values to get frequent changes. The edge information of a particular target pixel is examined by determining the brightness level of the neighborhood pixels. If there is no major difference in the brightness levels, then there is no probability of an edge in the image. Kirsch's template [18] is used for the extraction of blood vessels from retinal images. The Kirsch's template uses a single mask of size 3 × 3 and rotates at 45° increments through each of the eight directions. The edge magnitude of the Kirsch's operator is calculated as the maximum magnitude across all direction. The matrix contains the information of a pixel and its neighbors. The Kirsch's algorithm detects the edge and its direction. Accordingly, there are eight possible edge identification directions, such as the south, east, north, west, northeast, southeast, southwest, and northwest as shown in figure 4. Kirsch's template can set and reset the threshold values to obtain the most appropriate edges in the images. Kirsch's template works well for images having a clear distinction between the foreground and background, since the retinal blood vessels are considered as required foreground information in fundus images.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ 3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

Figure 4: Kirsch's Convolutional Kernel
The procedure of Kirsch's template is described as follows:

1. Detection: Apply Kirsch's template to the input retinal image and establish a rule to check the condition for edge detection. If it finds positive, then it can execute the condition further
2. False edge removal: If the condition is not fulfilled, at that point the algorithm cannot proceed
3. Vessel junction restoration: Fix broken junctions introduced by Kirsch's template. At the broken junction, track the direction of a vessel. Extend the vessel in the opposite direction for a certain length. On the off chance that another vessel is found, then bridge the gap and reestablish the vessel junction
4. Vessel labeling: A typical vessel is represented by two parallel edges. Vessel labeling fills the interior pixels of a vessel. The challenging task is to differentiate the area within a vessel and the area between the two different vessels that are parallel to each other.

3.4 Computing area of Microanesyms and Haemorhages

After removing blood vessels from the original image using morphological close operation the resultant image is binarised. Different morphological operations are applied on the resultant image to find the biggest circle and removing it

from the image. Then we have performed exeudates detection using morphological dilate, erosion and reconstruct methods. Microanesyms image is obtained by removing blood vessels and exeudates from the preprocessed image
Binarise the Microanesyms image and compute the area using regionprops. If the area is less than certain threshold then it is considered as Micronesyms and if the area is greater than certain threshold then it is considered as Haemorhages

3.5 Features Extraction

Along with the area of Microanesyms and Haemorhages different features such as Gabor and LBP are used for Diabetic Retinopathy detection and grading.

Gabor Features Extraction

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for texture analysis, which means that it basically analyzes whether there are any specific frequency content in the image in specific directions in a localized region around the point or region of analysis. Frequency and orientation representations of Gabor filters are claimed by many contemporary vision scientists to be similar to those of the human visual system, though there is no empirical evidence and no functional rationale to support the idea. They have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

Local Binary Pattern

The LBP feature vector, in its simplest form, is created in the following manner:

1. Divide the examined window into cells (e.g. 16x16 pixels for each cell).
2. For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
3. Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
4. Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.
5. Optionally normalize the histogram.
6. Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

3.6 Classification/Grading

The evaluate the performance of the system different supervised learning algorithms evaluated are

- Support Vector Machines
- K Nearest Neighbours
- Neural Networks
- Naïve Bayes
- Decision Trees

4. RESULT ANALYSIS

In this paper, IDRiD (Indian Diabetic Retinopathy Image Dataset [19] 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). It is essential to decide the need for treatment and follow-up recommendations.

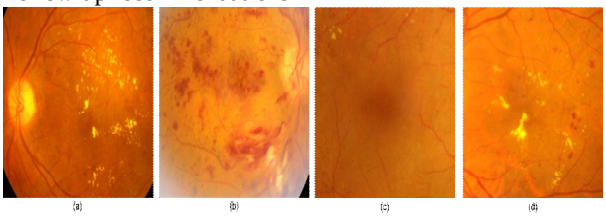

Figure 4: Phases of diabetic Retinopathy

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*)

Matlab-based GUI-driven tool is developed for effective detection and grading of diabetic retinopathy. GUI for this software is divided into number of subgroups according to their functionality. This software module not only detects diabetic retinopathy but also helpful in grading DR images for analysis and classification of diabetic retinopathy. 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)
After evaluating the performance of the system Gabor features with Naïve Bayes Classification gives better performance for Diabetic retinopathy detection and grading. Table 1 depicts the accuracy measure for LBP and Gabor features.

Table 1: Accuracy

	CT	NN	SVM	KNN	NB
LBP	60.992	51.77	50.3546	71.6312	41.844
Gabor	65.957	65.95	74.4681	73.0496	**77.8571**

Figure 5 shows the pictorial representation of performance evaluation for different classification techniques.

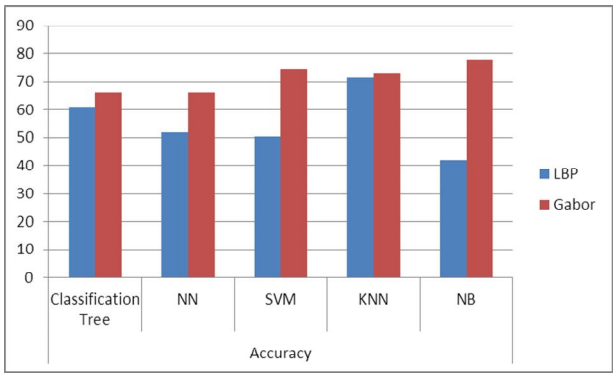

Figure 5: Performance Evaluation of Diabetic Retinopathy Detection and Grading

Table 2 depicts the performance of the proposed system using recall measure

Table 2: Recall

	CT	NN	SVM	KNN	NB
LBP	0.6586	0.5291	0.4729	0.7801	0.4504
Gabor	0.7072	0.6911	0.815	0.7909	0.8286

Table 3 depicts the performance of the system using precision

Table 3: Preision

	CT	NN	SVM	KNN	NB
LBP	0.6442	0.5314	0.4901	0.7281	0.5199
Gabor	0.6877	0.6751	0.803	0.7527	0.783

Table 4 depicts the perforamnce of the system using F measure.

Table 4: F measure

	CT	NN	SVM	KNN	NB
LBP	0.6513	0.5303	0.4814	0.7532	0.4827
Gabor	0.6973	0.683	0.809	0.7713	0.8051

5. CONCLUSION

This research work proposes a system for DR detection and classification at different stages. Preprocessing is an essential step at lesion level image segmentation for DR classification. CLAHE is used for the preprocessing of retinal digital. Further, in the stat-of-art methods, Kirsch's template technique is used for vessels extraction. Optic Disc is removed from retinal image using morphological operations. After performing optic disc removal and blood vessels segmentation, area of microanenysms and harorhages is detected which is used as a features for DR detection.To strengthen the reliability, these area features and Gabor/ LBP features are ensemble for the accurate classification of DR retinal images in different grading. For classification purpose, multi-class SVM, KNN, Naïve Bayes ,Neural networks and Decision trees were used. The proposed approach is validated on publically available database namely IDRiD. The average accuracy of Naïve Bayes Classifier with Gabor features is better. Collectively results are shown in the results section.
In the present work, more emphasis is given for segmentation of various features like blood vessels, location of OD, OD boundary, macula, hemorrhages and exudates from the retinal images in the Non-proliferative stage of Diabetic Retinopathy. Further, there is a scope to extend this work in the area of proliferative stage of Diabetic Retinopathy. The images from the standard databases are used for evaluation purpose. The real time images can be used for evaluation with the assistance of expert ophthalmologists. It is further suggested that the future extension of this work may consider the segmentation of other abnormal features like drusen, cotton wool spot etc. during the development of an automatic screening system of DR

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19. IDRiD (Indian Diabetic Retinopathy Image Dataset This dataset was available as a part of "Diabetic Retinopathy: Segmentation and Grading Challenge" organised in conjuction with IEEE International Symposium on Biomedical Imaging (ISBI-2018), Washington D.C.