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A Survey on Different Classifiers for Medical Diagnosis and Grading: Application to Diabetic Retinopathy

[1]Mamatha.B.V, [2]Srilatha L Rao, [3]Deepashree Devaraj, [4]Dr.S.C.Prasanna Kumar

[1,2,3,4] Department of Instrumentation Technology, RVCE, India

***Abstract*: In many parts of the world Diabetic Retinopathy (DR) causes serious problems related to health. There is a need in the medical community system for the early screening of the eye in order to detect the diseases that cause the blindness (Eg: DR). This aided as a motivation for many people who worked on the automated system for the analysis of the retinal images by using the image processing techniques. These features are utilized by the classifiers to grade DR into different stages according to the disease condition and thus indicating the severity. This paper aims at study of the different classifiers that can be used for the grading of DR.**

***Keywords*: Classifiers, Artificial neural network, Support vector machine, test set, training set, Fuzzy logic, Multilayer perceptron, Back propagation algorithm, hidden layers.**

I. INTRODUCTION

Diabetic Retinopathy is caused due to the vascular disorder affecting the retina due to prolonged Diabetes. It can lead to sudden vision loss in advance stages. It is the sixth largest cause of blindness among the people of working age in India, making it the world's diabetic capital. DR is responsible for 4.8% of the 37 million cases of blindness in the world [4]. It is estimated that there will be 360 million Diabetes cases in the world by 2030 [5]. After 15 years, 2% of patients with Diabetes will become blind, and 10% will develop severe vision loss. After 20 years, more than 75% of patients with Diabetes will develop some form of DR [4]. Consequently DR is expected to pose a significant health care challenge throughout the world. Routine screening and timely diagnosis can reduce the chances of severe vision loss by 95%.

Ophthalmologists conduct the diagnosis of diabetic retinopathy by taking the retinal images of the patients using the fundus camera. This process is a very time consuming task even for an outstanding ophthalmologist. For fully automated mass screen process a computerized screening system can be used. Such systems screen a large number of retinal images and identify abnormal images, which are then further examined by an ophthalmologist. This would save a significant amount of workload and time for ophthalmologists, allowing them to concentrate their resources on surgery and treatment.

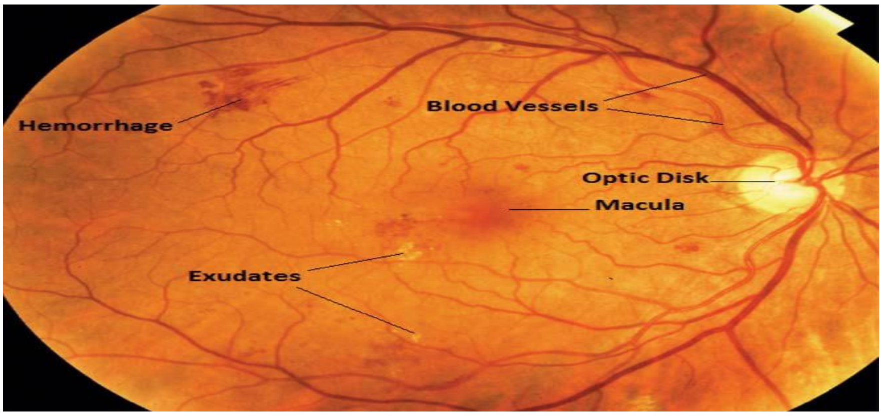

Fig 1: Anatomical structure of Retina [7]

Fig. 1 illustrates the symptoms of diabetic retinopathy of a retinal fundus image. The structure of retina includes blood vessel, optic disk and macula [7]. One of the stages in diabetic retinopathy is Non- Proliferative Diabetic Retinopathy (NPDR), which in this stage, the proliferative of blood vessels does not occur. Lesions of diabetic retinopathy consist of dark and bright lesions. The dark lesions comprise of microaneurysms and hemorrhages, and the bright lesions include exudates which are yellow deposits of lipid and protein that leak from the capillaries. The features of these lesions contribute to the classification of DR.

In recent years many people have presented the Computer aided detection (CAD) system which can analyze the retinal images and then classify them based on the abnormalities present. These systems utilize different features of the retinal image which are extracted after the preprocessing stage. The basis of the classification of different stages of diabetic retinopathy is the detection and quantification of blood vessels and hemorrhages present in the retinal image.

This paper is organized as follows; Section II discusses the preprocessing steps that are to be performed prior to the feature extraction and then a brief discussion of the various types of the classifiers in Section III, followed by the conclusion in section IV.

II. IMAGE PREPROCESSING

The workflow for the classification of DR is given in the form of block diagram in Fig 2. Diabetic retinal images used for the study of the features are from the Databases such as DIARETDB1, DIARETDB0 (Standard Diabetic Retinopathy Database Calibration level 0), STARE, DRIVE, MESSIDOR etc. These are the public databases used for the marking the diabetic retinopathy detection from the digital images. The images were captured with unknown camera settings and a particular field of view.

Image pre-processing deals with enhancing data images prior to computational processing. It can significantly increase the reliability and efficiency of CAD system. Initially the RGB image is converted to Gray scale image. To remove the problems caused by the bad illumination, digital filters are applied on the image.

Usually median filter is used since it has got excellent noise reduction capabilities than the linear filters of similar size. Exudates are the bright areas of comparatively high contrast than the neighbouring pixels. If median filter is applied to this, the filtered image will have exudates which are blurred to great extent. In addition to this, the optic disc which has the same intensity as the exudate also gets blurred. This filtering operation also preserves the sharpness of the edge of the image and also it produces the regions of constant intensity.

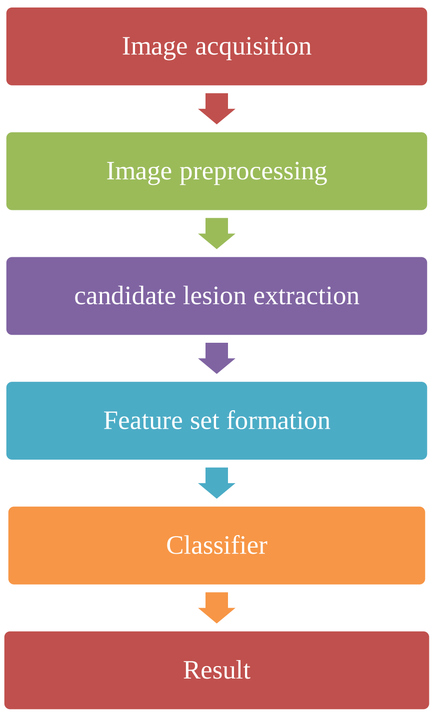

Fig 2: Block diagram

For Contrast enhancement, the Contrast Limited Adaptive Histogram Equalisation is applied (CLAHE). In this method, the image has small regions wherein the contrast is enhanced in each of these small regions using histogram equalisation. After performing the equalisations the neighbouring pixels are combined by using the bilinear interpolation. Since exudates and optic disc exhibits high intensity, contrast enhancement technique assigns them the high values. Fig 3a and 3b displays the histograms of the image before and after the application of CLAHE.

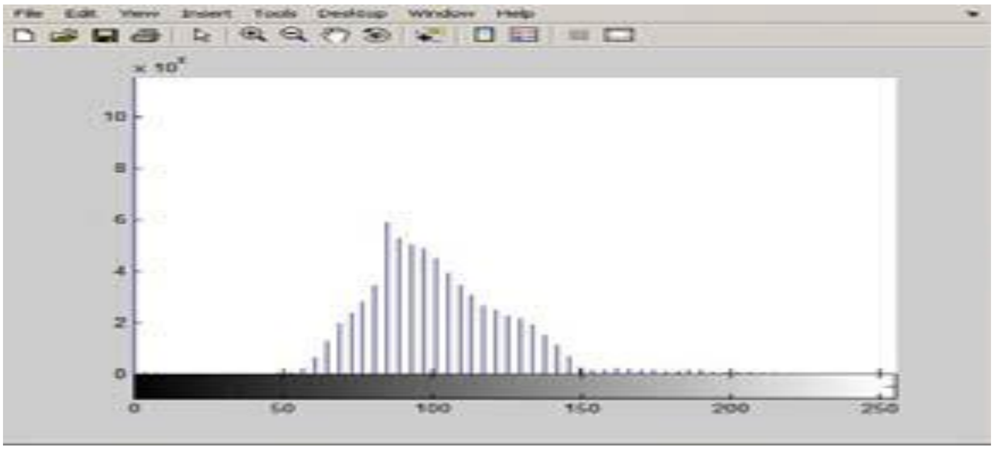

Fig 3a: Histogram before CLAHE [1]

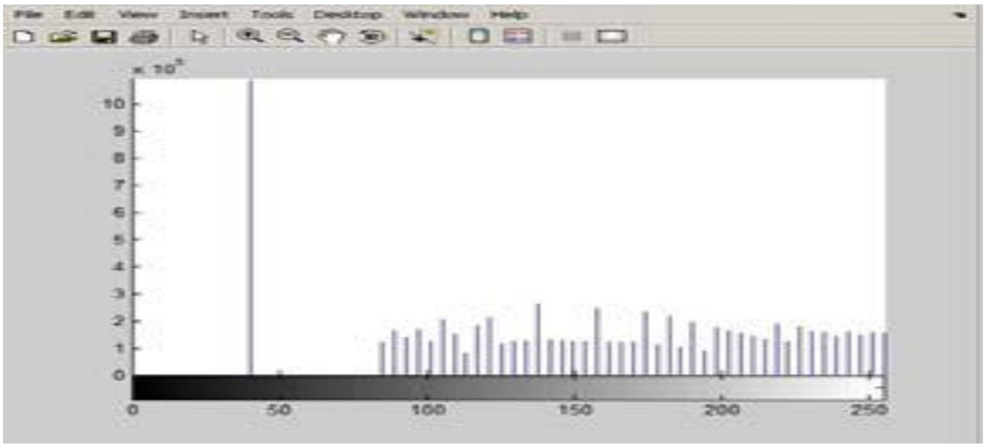

Fig 3b: Histogram after CLAHE [1]

Optic disc removal should be done before the detection of the exudates since they have the same intensity, colour and contrast as the exudates. Optic disc is the largest high contrast circular object in the retinal image. By using the masking operation, this task can be achieved.Blood vessels are removed by using the canny algorithm and applying gradient magnitude. The results are as follows.

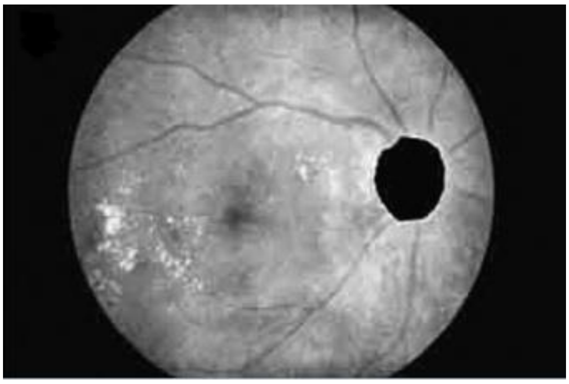

Fig 4a: Optic disc removal [2] **Fig 4b: Blood vessels [3]**

Finally the exudates are detected. Various imaging techniques can be used for the extraction of the hard exudates such as clustering, Morphological operations, Region splitting and Growing algorithm and Adaptive thresholding. The features are extracted from these detected lesions and then the classification is done. Figure below shows the original image and the exudate segmented image

Fig 5a: Original image **Fig 5b: Exudate segmentation**

III. DIFERRENT CLASSIFIERS USED FOR GRADING

The features of the extracted exudates are used by the classifiers to classify the different stages of diabetic retinopathy. Few of the classifiers employed by various authors are discussed in this section.

A. Back Propagation Neural Network

Ming You et.al [3] proposed an algorithm which used the back propagation concept of neural network. The features of the exudates that are used for this algorithm are the contrast of the image, homogeneity, area of the blood vessels and the area of the exudates. Figure 6 shows the basic structure of the BP neural network. Here, X_j is the input vector, α and θ are the threshold functions, O_j is the output vector, W_{ij} is the weight vector.

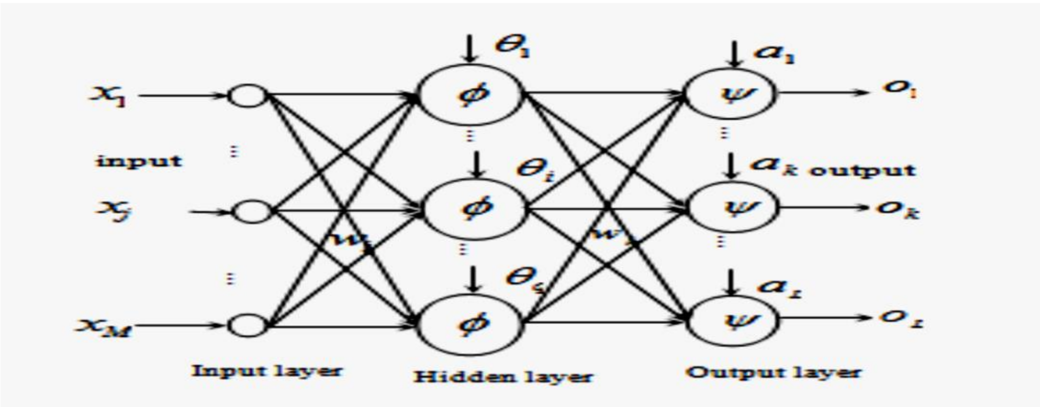

Fig 6: Structure of BP network [3]

Back propagation learning process consists of two aspects, Forward propagation signal and Backward propagation of the error signal. During the forward propagation of the signal, the input signal is propagated from the input layer , the it passes through the hidden layer and finally reaches the output layer. The values of the weight and the threshold are kept constant. Error signal is the difference between the actual output and the expected output, it is propagated from the output layer to the input layer. During this layer-by-layer propagation, the weight value of the network is regulated to make the actual output of the system closer to the expected output. When the error is greater than expected, the weight value and the threshold value are needed to be modified; the gradient descent method is adopted to regulate Weight Value and Threshold Value. BP neural networks model which are used here are neural network consisted of an input layer (4 nodes), one hidden layer (12 nodes), and an output layer (1 node). The neural network was trained by using 5,000 iterations. This is simulated using MATLAB. Images are classified in to four classes where class 1 for normal images, class2 belongs to NPDR (Non Prolifertive Dibetic Retinopthy), class 3 for images belongs to PDR (Prolifertive Dibetic Retinopthy). A training set of 70 values and testing set of 50 values are used.

B. Support Vector Machine

The aim of the support vector machine is to find the optimum hyperplane which seperates the two classes with the largest margin[8].

Figure below shows the separation of two classes with the help of SVM.

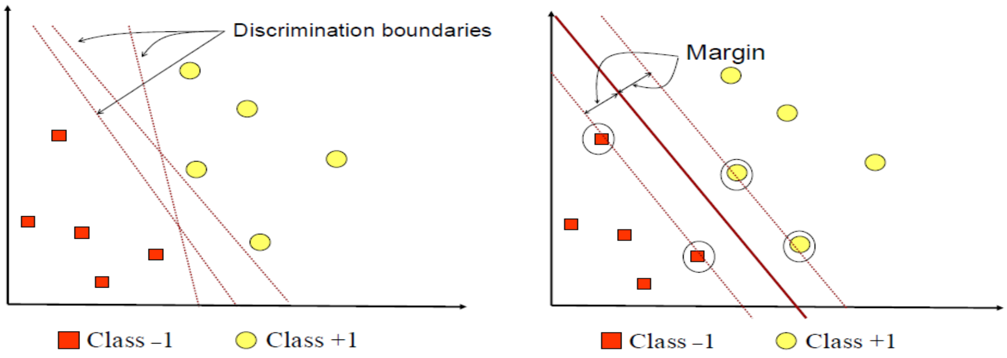

Fig 7a: Hyperplane of SVM [8]

The hyperplane function is defined as, F(x)=w.x+b=0--------------------------------(1)

Where x is the input vector, w is the weight and b defines the bias. Soft margin SVM allow misclassify data by introducing a slack variable $\varepsilon_i \geq 0$, i= 1,..., n. and penalty. As illustrated in Fig. 7b, the slack variable value for the correctly classified data is $\varepsilon_i = 0$. The data that are incorrectly classified have the slack variable value $\varepsilon_i \geq 1$. The sum of error score (slack variable) is multiplied by C. The score of C defines the trade-off between maximum margin and the error that are tolerated. The feature vector consists of four features; area, perimeter, centroid and standard deviation related to the exudate detection. 147 retinal images were used for classification, then the data set is divided into test data and the training data. Training set is used for the SVM classification model and the test set is used for the validation.

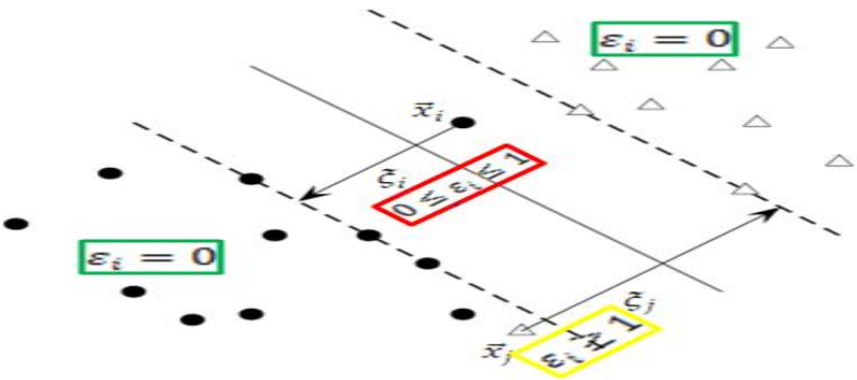

Fig 7b: SVM with slack variable [8]

C. Wavelet Based Neural Network

Color retinal images with the resolution 3872x2592 were used in this method. Initially the images were resized and pre processed. Higher the spatial resolution more pixels are used to display the image resized. Normal size is reduced to 33x50 pixels. Resized images were gray scaled. Then the wavelet transform is used to extract the features before classifying the images. Single level discrete wavelet transform is applied with respect to either a particular wavelet or particular wavelet decomposition. This will calculate the coefficient matrices obtained by the wavelet decomposition of the input matrix. Using this transform, matrix consisting of 8x13 resolutions is obtained. Optimum normalization is obtained after dividing by 255. These wavelet features were taken as input for the multilayer neural network. The structure of multi-layer perceptron (MLP) is like 13:8:6, which means 13 neurons of input layer, 8 neurons of hidden layer, and 6 neurons of output layer. Totally 30 data sets have been used for the training and only 3 images were used for testing.

D. Multilayer Perceptron Back propagation

Multilayered perceptron back propagation algorithm is used as classifier by Saketh and et.al [1]. Three different feature were used as the input vectors for the MLP. Area of the ON pixels which is the total sum of the pixels in the binary image with the value as 1,Mean and the sum of the exudates which is the total area of the exudate in the image. These features were fed to the multilayer perceptron neural network with 2 hidden layers, 100 samples, and 34 images for testing. This network has the accuracy of 94.11%, but it does not provide the desired results in the case of the exudates area at particular section of the fundus exceed that of optic disc.

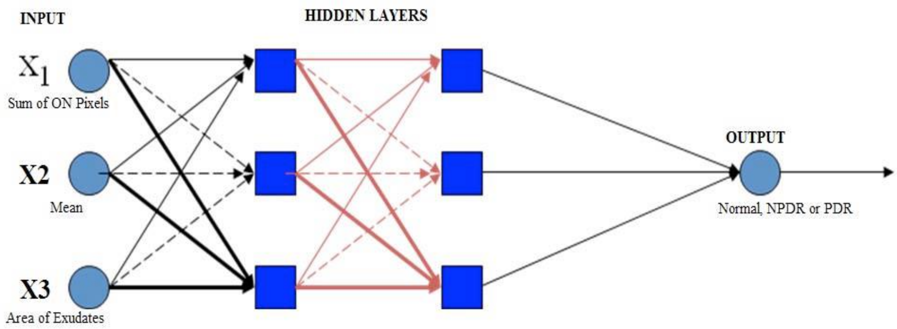

Fig 9: MLP architecture [1]

E. Bayesian Classifier

This is the classifier which is based on the probability. The classifier works on the basis of Bayes theorem with assumptions which are strong and independent. In more descriptive way, it can be termed as independent feature model. Bayes classifier assumes that the absence or the presence of any feature is not dependent on the absence or presence of any other feature. Naïve Bayes classifier uses the principle of maximum a posteriori (MAP) classification measure a finite set of features $\mathbf{x} = (x1, \ldots, xn)$ then select the class

$$y=\arg(\max P(x|y))$$

Where,

$$P(y|\mathbf{x}) \propto P(\mathbf{x}|y)P(y)$$

$P(\mathbf{x}|y)$ is the likelihood of feature vector **x** given class y, and $P(y)$ is the priori probability of class y. Naive Bayes assumes that the features are conditionally independent given the class:

$P(\mathbf{x}|y) = \Pi P(x|y)$

The parameters ( ) $P(x|y)$ and $P(y)$ are estimated from the training data. The feature set consisting of 18 features are used for the classification.

IV. CONCLUSION

On studying the various classifiers that are used for the classification of the retinal images as different stages of DR, the Support Vector machine (SVM) is agreed to be the best classifier which gives the results in good accuracy. Table1 compares the various characteristics like the number of features used for classification, training data and testing data etc. of the classifiers which are used for the classification.

Classifier used	Accuracy	No. of features	Database	Testing data	Training data
Basic Back propagation neural network	88.00%		DIARETDB0	70	50
Soft margin Support Vector Machine	90.54%	4	MESSIDOR	74	75
Wavelet based neural network	90.00%			3	30
Multilayer perceptron with Backpropagation	94.11%	29	University of Valladolid, Spain	50	50

Table 1: Comparison of different classifiers used for the classification of DR

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