Automatic Grading of Diabetic Retinopathy through Machine Learning

Supriya Sangappa Kamatgi, K. N. Hosur

Abstract: Diabetes Retinopathy (DR) illness refers to a group of eye issues that can happen because of diabetes. It's the medical phenomenon within which a person's retina is broken by the diabetes. During this stage the tinny blood vessels present within the retina get damaged due the high glucose level. This ends up damaging the tiny blood vessels within the retina leading to the loss of vision. Different complications occur due diabetes a number of them are upset, neuropathy, nephropathy, retinopathy, skin damages, hearing ailments. Globally, diabetic eye disease has become the fifth most common reason for blindness. Early identification of DR is important to forestall vision loss or blindness. In this paper the strategies like Naïve Bayes classifier, Bagged Decision Tree and Support vector machine are implemented and are used for the classification of data based on the training and testing datasets. The errors and accuracy of all the three classifiers are figured and the best among three is considered for the future application. This implementation is done in the MatLab software and results shows that the Bayes classifier gives the error 0.2, Bagged Decision Tree Classifier gives the error of 0.1 and the Support Vector machine gives the error of 0.04 is observed. Hence these observations shows that the Support Vector machines are good classifiers with the accuracy of 96%.

Keywords: Machine learning, Naïve Bayes Classifier, Bagged Decision Tree, Support Vector machine.

I. INTRODUCTION

Diabetic Retinopathy (DR is otherwise called the diabetic eye sickness. It is an ailment wherein there is harm to the tiny blood vessels that supplies to the retina [1]. Retina is the part of the eye where the image is formed, so it is very important for the retina to be free from any kind of lesions. In retinopathy, the blood vessels are weakened and may leak fluid and blood. It is the major cause of blindness. It is caused due to diabetes mellitus, both type 1 and type 2 diabetes can lead to diabetic retinopathy. Diabetes mellitus is rising as a significant general medical issue in India. It happens because of inadequately controlled glucose levels [2]. Diabetic retinopathy mainly affects the retina, it is the light sensitive area where the image formation occurs and also it plays a major role in vision.

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It is more commonly seen in working age group of adults, it influences up to 80 percent of the working populace who had diabetes for a long time or more [1]. In patients with over 20 years of diabetes, all the patients with type 1 diabetes i.e., insulin reliant and in excess of 60 percent of the patients with type 2 diabetes i.e., non-insulin ward will have some level of retinopathy.

Diabetic retinopathy can harm to the blood vessels due to the high blood glucose levels, and the aftereffect of this is the swelling and leakage of the blood vessels. Other people who are in danger of developing diabetic retinopathy are those patients who experiencing hypertension, high cholesterol, kidney illness and anemia [2].

There might be no indications in the beginning periods, particularly when the focal segment of the retina isn't included yet as the diabetic retinopathy advances the side effects, for example, the symptoms such as blurred vision may be seen. Hence early detection of the DR is a necessary task. In order to automation detection should be more accurate and error free. So, the best classifier is utilized to arrange the input image into an a diseased and a normal eye. In this project the strategies like Naïve Bayes classifier, Bagged Decision Tree and Support vector machine and are utilized for the grouping of information dependent on the preparation and testing datasets. The errors and accuracy of all the three classifiers are computed and the best among three is considered for the future application. This implementation is done in the MatLab software and inferred results shows that the Support Vector machine gives the most complete accuracy when compared to Naïve Bayes classifier and the Bagged Decision Tree and hence the error is less for Support Vector Machines.

II. LITERATURE SURVEY

This part subtleties with the different books, online material and the research papers that have added to the reviewing of the diabetic retinopathy. In this paper [1] author provides the detail steps involved in detection of exudates. Pre-preparing stage includes resizing of the picture, RGB to greyscale transformation filtering of image to remove the noise. In the segmentation phase Optic disk detection, blood vessels extraction and adaptive thresholding for exudates detection is done. The proposed algorithm works even on lower quality images. To identify different injuries in fundus pictures, for example, haemorrhages so as to analyse DR all the more adequately. In this paper [2] author gives explains about, pre-processing and segmentation which is done in CIE Lab colour space, the feature vector dependent on colour and texture is extracted from GLCM (Grey Level Co-occurrence Matrix). These feature vectors are used to classify the eye into exudates and non- exudates using KNN classifier.

Exudates were distinguished with 97% achievement rate. The proposed technique performs best by portioning significantly smaller area of exudates. In this paper [3] author gives explanations about the optic Disk which is detected using circular hough() transform. Maximum and minimum value of green and red channels is found. Mean of the two is found. Pixel value between sigma and 3-sigma is taken to be an exudate. Results of the algorithm are matched with manually marked exudates. A sensitivity of 99% is obtained. Manual selection of region is done in this method, which is a tedious process. In this paper [4] the author explains about, pre-processing of fundus image which is done to reduce noise. Optic disk, micro-aneurysms and exudates are separately extracted. Using the above features, classification between normal and abnormal fundus is done. Accuracy of the above algorithm is obtained to be 96%. In this algorithm, various features have been looked in. Due to this, the time required for computation is very high which is unsatisfactory. In this paper [5] the author fundus image analysis is done by colour normalization, edge enhancement, colour space conversion, binarization and feature extraction and Kernel based SVM Classification is implemented. Early analysis of DR by methods for fundus picture highlights achieved a precision of 91.2% and particularity of 92% by SVM classifier. It could be beneficial symptomatic strategy that masks faulty diagnosis. In this paper [6] the author explains about pre-processing and Erosion steps that are used at the initial stages to remove blood vessel and to get optic disc. Distance and watershed Transformation are used for detection of Exudates. 99% accuracy in detection of Exudates is achieved. In this paper [7] the author relays on automatic discovery of diabetic retinopathy through distinguishing exudates in colour fundus retinal images and also classifies the rigorousness of the lesions. Decision making of the seriousness level of the disease is determined by SVM classifier. In this paper [11] author gives a novel algorithm is proposed which can be used to determine macular swelling through reconstruction of a naive height map of the macula regions from various fundus images with an unknown translation (generally corresponding to the eye), captured by an un-calibrated fundus camera. They show how retina “blisters” can be identified, even in regions where there is no clear surface obvious utilizing four fundus pictures.

III. OPERATIONAL DEFINITION

A. Support Vector Machine (SVM)

The data can be classified in multidimensional space. SVM is a most common technique for data classification and regression. It divides the data in best possible way. It is explained by Vapnik [10] in details. The training data for pattern recognition is in the form

$$(x_1, y_1), \ldots\ldots\ldots, (x_e, y_e) \in R^n \times \{+1, -1 \qquad (1)$$

that is n–dimensional examples (vectors) xi and their names yi. A mark with the estimation of +1 signifies that the vector is arranged in class +1 and a name of −1 indicates that the vector is a piece of class −1. We consequently attempt to discover a capacity f(x) = y: $R^n \rightarrow \{+1, -1\}$ that separated from effectively ordering the examples in the preparation information accurately groups concealed examples as well. This is known as generalization. SVMs depend on the class of hyper planes

$$\langle w \,.\, x \rangle + b = 0; \text{ w } R^n, \text{ b} \in R^n \qquad (2)$$

Which essentially separate the information space into two: one section containing vectors of the class −1 and the other containing those that are a piece of class +1 as appeared in figure 1. In the event that there exists such a hyperplane, the information is supposed to be straightly divisible. To discover the class of a specific vector x, we utilize the accompanying choice capacity

$$f(x) = \text{sign}\,(\langle w \,.\, x \rangle + b) \qquad (3)$$

There might be more than one hyperplane that effectively orders the preparation models (for example, in Figure. 1 the hyperplane could be nearer to class −1). It has been indicated that the hyperplane that ensures the best speculation execution is the one with the maximal edge of partition between the two classes. This kind of hyperplane is known as the ideal or maximal edge hyperplane and is special.

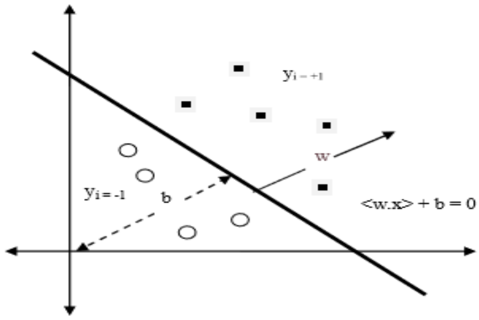


Figure.1. A separating hyperplane (w, b) for a two-dimensional (2D) training set

The ideal hyperplane can be built by settling an arched (no neighborhood minima, consequently any arrangement is worldwide) improvement issue that is limiting a quadratic capacity under direct disparity limitations. The answer for this issue has a development regarding a subset of the preparation models that lie on the edge, called support vectors as appeared in Figure.2.

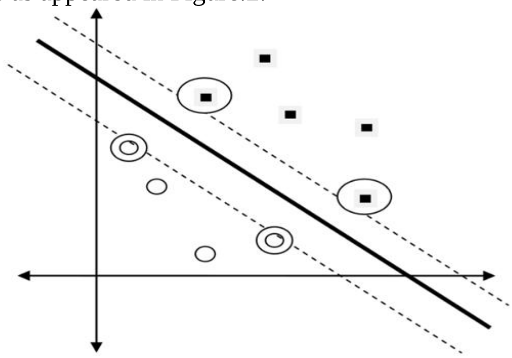


Figure. 2 A maximal margin hyperplane with its support vectors encircle

Support vectors contain all the data required about the characterization issue, since regardless of whether the various vectors are expelled the arrangement will in any case be the equivalent, the optimization problem (used to locate the ideal hyperplane) and the decision function can be expressed in dual form which relies only on dot products between vectors. The dual representation of the decision function is

$$f(x) = \text{sign}\left[\sum_{i=1}^{l} \boldsymbol{y_i \alpha_i \langle x \,.\, x_i + b \rangle}\right] \qquad (4)$$

Where,

$\boldsymbol{\alpha_i} \in$ R is a real valued variable that can be seen as a proportion of how much informational worth xi has.

Thus in this manner for vectors that don't lie on the edge (for example non bolster vectors) this value will be zero. The ideal hyperplane classifier utilizes just dot products between vectors in input space. In feature space this will translate to $\langle \boldsymbol{\varphi}(\boldsymbol{x}).\boldsymbol{\varphi}(\boldsymbol{y}) \rangle$. A kernel is a function K(x, y) that given two vectors in input space, returns the dot product of their images in feature space as shown in Figure. 3. In this manner, K(x, y) = $\langle \boldsymbol{\varphi}(\boldsymbol{x}).\boldsymbol{\varphi}(\boldsymbol{y}) \rangle$. To build an ideal hyperplane, SVM utilizes an iterative preparing algorithm, which is used to minimize an error function. SVM preparing includes the minimization of the error function,

$$\frac{1}{2}\, w^T\, w + C\, \sum_{i=1}^{N} \xi_i \qquad (5)$$

Subjected to requirements,

$$y_i\, (w^t\, \varphi(\, x_i) + b)\ \geq 1 - \ \xi_i \qquad (6)$$

And

$$\xi_i\ \geq 0, i = 1 \ldots N \qquad (7)$$

where, C - limit constant, w - vector of coefficients, b a constant and ξ_i are boundaries for taking care of non-divisible information (inputs). N is the training case with index i. $y \in\ \pm 1$ is the class names and x_i is the independent variables. The kernel φ is utilized to change information from the input (autonomous) to the feature space. The polynomial kernel which is given by,

$$\mathrm{K}\ (x, x') = (x.x' + 1)^d \qquad (8)$$

where, x and x' are the element vectors for the three classes, d is the kernel parameter. Support vector machine preparing process is applied to break down preparing information to locate an ideal method to arrange pictures into their separate classes. The non-linear mapping from input space to feature space is shown in figure 3.3. The size of the information preparing vector is 250 * 6. The yield can be one of the three classes to be specific typical, NPDR and PDR.

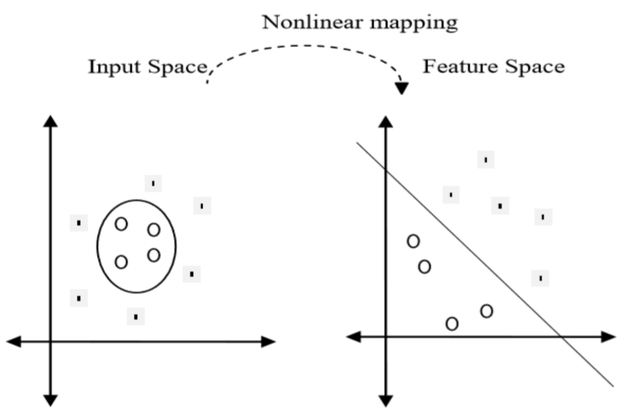
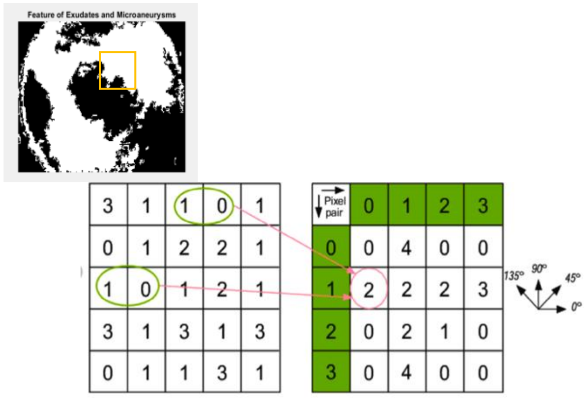


Figure.3 A nonlinear mapping from the input space to feature space

B. Grey Level Co-occurrence Matrix

It contains data about the places of pixels having comparable dark level qualities. It can utilize separation vector. As a name recommends co-event along these lines, this implies two items need to happen all the while together and we are simply going to quantify how synchronous is their event as appeared in figure. 4.

Consider the picture (underneath left). On the off chance that we utilize the position operator "1 pixel to the right and 1 pixel down" then we get the gray-level co-occurrence matrix (below right).



$$\begin{matrix} 0 & 0 & 0 & 1 & 2 \\ 1 & 1 & 0 & 1 & 1 \\ 2 & 2 & 1 & 0 & 0 \\ 1 & 1 & 0 & 2 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{matrix} \qquad C = \frac{1}{16} \begin{bmatrix} 4 & 2 & 1 \\ 2 & 3 & 2 \\ 0 & 2 & 0 \end{bmatrix}$$

Figure. 4 Creating a GLCM lattice from image

where an entry cij is a check of the occasions that F(x,y) = i and F(x + 1, y + 1) = j. For instance, the principal passage originates from the way that multiple times a 0 shows up beneath and to one side of another 0. The factor 1/16 is on the grounds that there are 16 sets going into this framework, so this standardizes the grid sections to be appraisals of the co-event probabilities.
For statistical confidence in the estimation of the joint likelihood dispersion, the framework must contain a sensibly enormous average occupancy level.
Accomplished either by (a) confining the quantity of adequacy quantization levels (causes loss of precision for low-sufficiency surface), or (b) utilizing huge estimation window (Causes blunders if surface changes over the huge window).
Average trade off: 16 dim levels and window size of 30 or 50 pixels on each side. Presently we can dissect C:
Maximum extreme likelihood passage component contrast

$$k{:}\, \sum_i \sum_j\ (i - j)^k c_{ij} \qquad (9)$$

This descriptor has moderately low qualities when the high estimations of c are close to the principle diagonal. For this position operator, high qualities close to the principle diagonal would show that groups of constant intensity running "1 pixel to the right and 1 down" are likely. When k = 2, it is known as the contrast:

$$\text{Contrast} = \ \sum_i \sum_j\ (i - j)^2 c_{ij} \qquad (10)$$

$$\text{Entropy} = -\ \sum_i \sum_j\ c_{ij} \log c_{ij} \qquad (11)$$

This is a proportion of haphazardness, having its most elevated worth when the components of C are altogether equivalent. On account of a checkerboard, the entropy would be low.

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$$\begin{matrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{matrix} \rightarrow \begin{bmatrix} 8 & 0 \\ 0 & 8 \end{bmatrix}$$

$$\text{Uniformity (also called Energy)} = \sum_i \sum_j {c_{ij}}^2 \qquad (12)$$

(littlest value when all entries are equivalent)

$$\text{Homogeneity} = \sum_i \sum_j \frac{c_{ij}}{1+|i-j|} \qquad (13)$$

(enormous if huge qualities are on the primary diagonal)

C. Naïve Bayes Classifier

The Naïve Bayes classifier belonging to the group of probabilistic classifiers based on applying Bayes theorem with strong independence assumptions between the features. It is the simple technique for constructing classifiers. The informational index is isolated into two sections to be specific, feature matrix and the response vector.

1. Feature have the vectors of dataset in which every vector comprises of the estimation of dependent features.
2. the estimation of class variable for each lines of feature matrix is present in the response vector.

Naive Bayes model is handy to build and especially valuable for enormous data sets. Along with straightforwardness, Naive Bayes is known to beat even profoundly modern order methods. Bayes gives a method of figuring back likelihood P(c|x) from P(c), P(x) and P(x|c). consider the equation below:

$$P(c/x) = \frac{P\left(\frac{x}{c}\right)P(c)}{P(x)} \qquad (14)$$

Above,

1. *P*(*c*|*x*) is the back likelihood of class (c, *target*) given predictor (x, properties/ attributes).
2. *P*(*c*) is the earlier likelihood of class.
3. *P*(*x*|*c*) is the likelihood which is the likelihood of predictor given class.
4. *P(x)* is the earlier likelihood of predictor.

D. Bagged Decision Tree

Bagging is a basic and incredible ensemble method. An ensemble is a method that joins the forecasts from various AI and machine learning calculations together to make more exact expectations than any individual model. Decision trees are sensitive to the particular information on which they are prepared. In the event that the preparation information is changed the subsequent choice tree can be very unique and thus forecasts in turn can be quite different.

Let us assume we have an example dataset of 1000 occasions (x)

and we are utilizing the CART algorithm. packing of the CART calculation would function as follows.

1. Make many (e.g.100) arbitrary sub-tests of our dataset with substitution.
2. Train a CART model on each example.
3. Give another dataset, figure the average prediction from each model.

IV. METHODOLOGY

The block diagram for the proposed work employed is shown in figure. 5. At first the at most significant assignment is to gather the suitable information and determination of the software for the handling. After the required initial task the next task is to eliminate the optic disk from the fundus image and then the blood vessels are removed so as to distinguish the exudates.

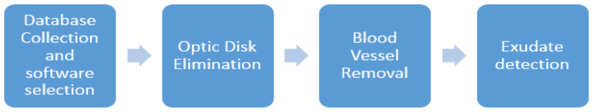


Figure. 5: Block diagram of the methodology

The flowchart of the program for the proposed work is as appeared in figure. 6.

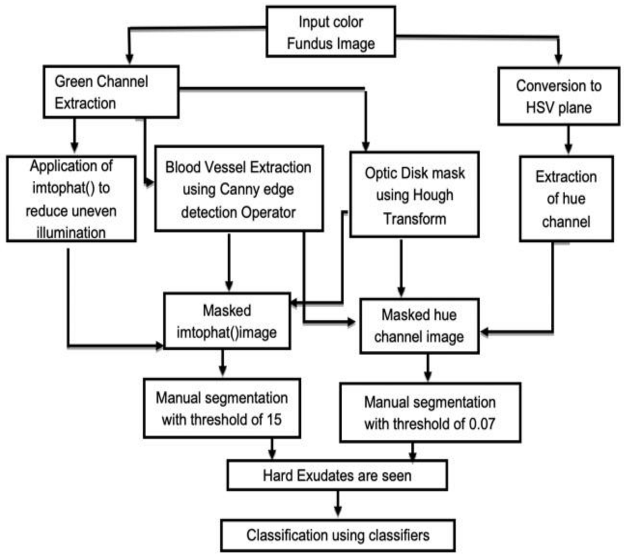


Figure. 6: Algorithm of the developed code

A. Database Collection and Software Selection

Fundus images from online database DIARET are employed as show in below figure 7, for examining the work. The database consists of 140 fundus images. MatLab was used to develop the code as it is simple to use for research purpose.

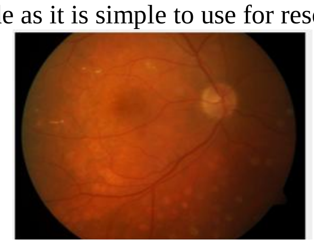


Figure. 7: Colour fundus picture

B. Location and Removal of Optic Disk

The pixel intensity of Optic Disk is in the same range as that of exudates, so Optic Disk has to be removed for better detection of exudates. The exudates and optic disc are as shown in below figure 8.

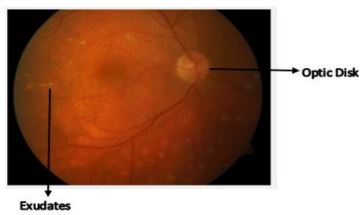


Fig. 8: Optic Disk and Exudates in a fundus image are marked

Optic Disk is eliminated using Hough transform principle. Hough transform is employed in MatLab to provides the positions of centres of different circles of radii in the range of 20-25 units. The function is applied on the green channel of the colour fundus images. Two matrices are obtained. First is a n x 2 matrix, here, n is number of circles in the image, giving co-ordinates of centre of circle, and other is a n x 1 matrix, that gives radius of each circle. The pixel intensity at the co-ordinates is looked at, and the most noteworthy among them is taken to be the focal point of the Optic Disk. Sometimes, the pixel intensity at the co-ordinates can be as low as that of blood vessels, to reduce this confusion, a 20 x 20, matrix is made, of which the centre is the co-ordinate pixel. Then, the intensities of pixels in the matrix are compared, whichever pixel is highest, that is taken to be the centre of Optic Disk. Then a mask of 30 units is created around the centre co-ordinates. The function, hypot() is used in creation of the circle. The circle is superimposed on the fundus image, eliminating the Optic Disk.

C. Blood Vessels Elimination

Elimination of blood vessels is an important step. Blood Vessels are eliminated by application of various processes. Canny edge operator is applied to green channel of colour fundus images. This new image gives edges of image obtained using the operator as shown in figure.9.

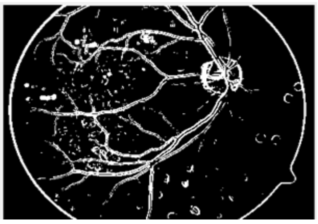


Figure.9 Edges of image obtained using canny edge detector Operator

The edges are filled in by dilation operation. Then, the obtained image is manually segmented. If the pixel intensity in green channel image is less than 50, then the pixel is retained, else removed. The blood vessels are extracted and they appears as shown below in figure 10.

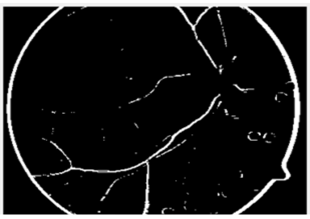


Figure.10 Extracted Blood Vessels

D. Detection Of Exudates

Early detection of exudates in diabetic patients reduces the severity of treatment. Hue channel of HSV plane provides the primary colour, without its brightness. HSV (Hue, Saturation and Value)plane is first obtained by application of 'rgb2hsv ()' function. Hue channel, from HSV plane can be easily extracted. Optic disk and blood vessels from the Hue channel are eliminated. Uneven illumination of green channel is reduced and the Hue channel images are manually threshold as shown in figure 11.

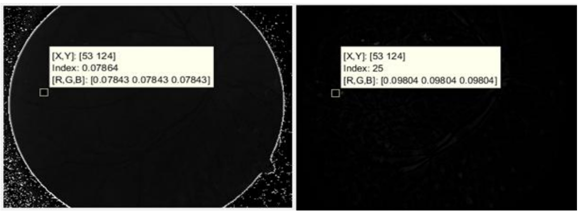


Figure. 11 Manual selection of threshold values

The resultant image obtained contains the exudates. The result is compared with manually marked image by specialists. The fundus image marked by specialist is as shown in below figure 12. The marked image contains markings for different lesions. Exudates are marked with a light green mark.

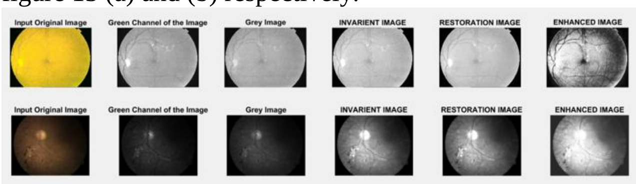
Figure. 12 Fundus image marked by specialists

V. RESULTS AND ANALYSIS

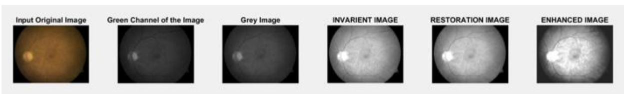
DIARET database (open source) is used which consists of 140 color fundus images. The Proposed technique was actualized in Matlab and Microsoft Visual Basic 6.0. The results of the initial stages such as preprocessing and detection of exudates is done followed by classification of the fundus using machine learning technique such as support vector machine, Naïve Bayes classifier and Bagged Decision Tree.

A. Pre-processing

In order to remove all the abnormalities associated with the input image preprocessing is required. This stage involves the process such as conversion to color space, green channel extraction, invariant, restoration and enhancement. The fundus has to be preprocessing so as to remove the unevenness that is being present in the illumination, to filter the noise that is being induced while taking the fundus of an eye and also there is no enough contrast among the exudates and the image background. The yield aftereffect of the preprocessing steps of DR and normal eye are shown in figure 13 (a) and (b) respectively.



(a)



(b)

Figure.13 (a) Preprocessing Output of Diabetic Retinopathy Eye and (b) Preprocessing of the Normal Eye

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From the outset the info RGB image is changed over to the grey level image in order to obtain the binary values of the pixels and now in order to remove noise the median filter is applied to it and is called as restored image, to modify the complexity of the image histogram equalization is applied to the restored image and is called as enhanced image and to evacuate uneven illumination, image adjust operation is applied on the enhanced image and is called as invariant image.

B. Detection of Exudates

The preprocessed picture is then used to distinguish the exudates by performing optic circle elimination followed by blood vessels removal and then recognizing the exudates.
The figure 14 gives the pictures of the exudates for both the typical and the diabetic retinopathy eye. These pictures are utilized for additional handling to identify and categorize them as an ordinary eye or diabetic retinopathy and furthermore to distinguish is it a genuine harm (sever or moderate) or the beginning periods of DR.
Optic disc is eliminated by Hough Transform. A Success rate 92% is obtained. The figure 10 gives the means engaged with the discovery of the optic plate and afterward utilizing this data the optic circle is removed out in the following stage.

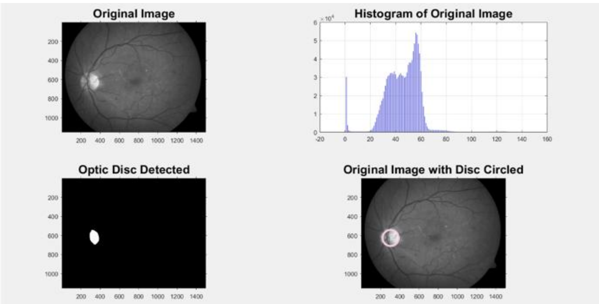

Figure. 14. Optic Disc Detection

The green channel of the image is generated and the disc circled image is used to obtain the masked image or the optic disc eliminated image as shown in figure 15.

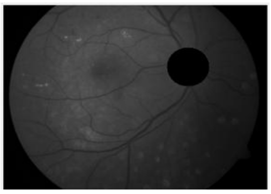

Figure. 15 Optic disc is masked

Blood Vessels are extracted using Canny Edge operator. The variations in the grey scale intensities of the image is recognized by canny edge operator and this variation can be found by determining gradients of the image and then manual segmentation is implemented. A threshold of 50 is used. The green channel image and extracted blood vessels image is as shown in below figures 16 and 17 respectively.

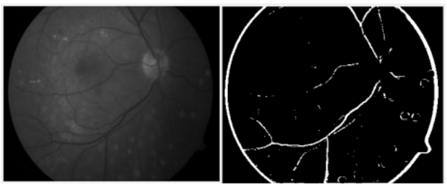

Figure.16 Green channel image, Fig.17 Blood vessels are extracted

HSV plane is first obtained by application of 'rgb2hsv ()' function. The HSV plane is as shown in figure 18. Hue plane is extracted before detection of the exudates in order to overcome uneven illumination related issues. The Hue channel of the image is as shown in figure 19.

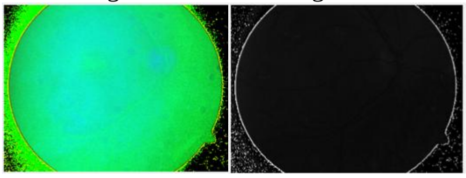

Figure.18 HSV plane, Figure.19 Hue channel is extracted

Hard Exudates are detected by manual segmentation of Hue channel and imtophat() image. The hard exudates are as shown in below figure 20.

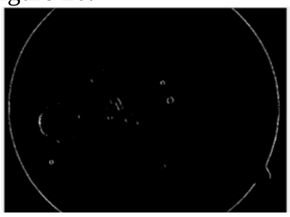

Figure.20 Hard Exudates are detected

Thus, hard exudates are detected with good accuracy using image processing techniques. High performance was observed especially in the green channel due to good contrast. The extracted features are then given to the classifiers to classify the data the figure 21 gives the predicted and observed model for the given data for the Naïve Bayes classifier. Also the data is classified using Bagged Decision Tress classifier.

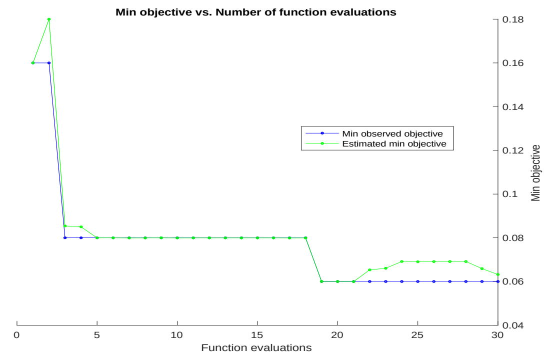

Figure. 21 Bayes Predicted Model

The percentage of confusion matrix off the diagonal for the Bagged Decision Tree is as shown in figure 22. The out-of-bag-feature importance and feature have been plotted.

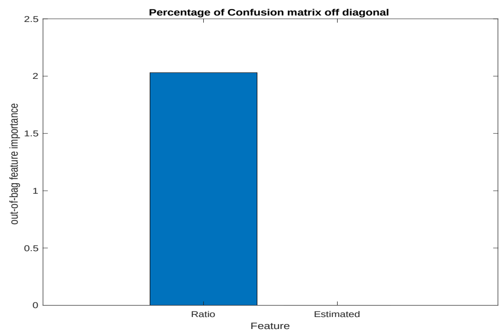

Figure. 22 Percentage of confusion matrix off the diagonal

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The ECOC support vectors is a blunder remedying yield codes classifier for multiclass realizing, where the classifier comprises of various binary learners, for example, SVM's. These classifiers are utilized to perform assignments, such as anticipating marks or posteriors probabilities for new information as appeared in figure.23.

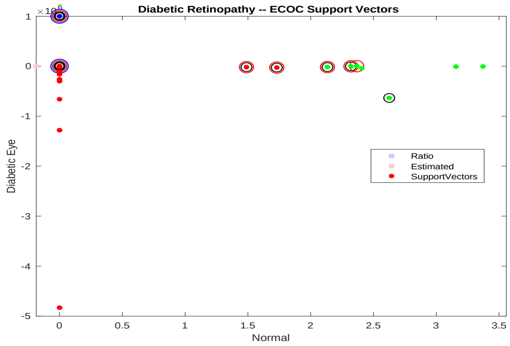

Figure.23 Diabetic Retinopathy ECOC Support vectors

The confusion matrix for the true class and predicted class is as shown in bellow figure 24. The matrix shows the complete number of perceptions in each call. The horizontal lines of the confusion matrix relates to the predicted class. Diagonal and off inclining cells compares to effectively and mistakenly grouped perceptions, individually.

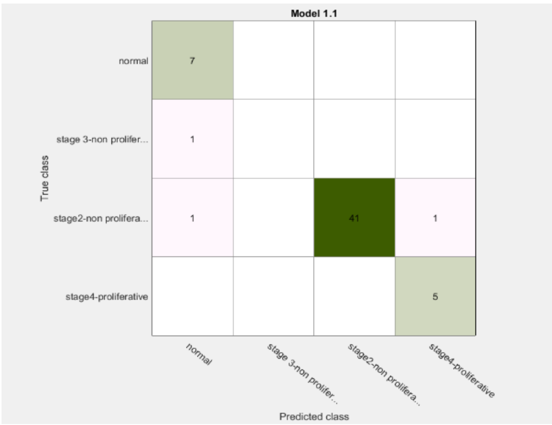

Figure.24. Confusion Matrix

It contains data about the places of pixels having comparable dark (grey) level qualities. It can utilize separation vector. GLCM for both normal eye and DR eye is as shown in below figure 25 and 26 respectively.

glcm

9x9 double

	1	2	3	4	5	6	7	8	9
1	295574	1205	0	0	0	0	0	0	0
2	1205	64774	8143	0	0	0	0	0	0
3	0	8143	464399	15587	0	0	0	0	0
4	0	0	15587	387788	15154	0	0	0	0
5	0	0	0	15154	402598	1150	0	0	0
6	0	0	0	0	1150	14819	445	0	0
7	0	0	0	0	0	445	3710	229	0
8	0	0	0	0	0	0	229	4941	336
9	0	0	0	0	0	0	0	336	3747
10									
11									

Fig.25. GLCM of Normal eye

glcm

9x9 double

	1	2	3	4	5	6	7	8	9
1	56262	641	97	57	45	22	7	2	0
2	613	256	87	71	65	60	47	23	1
3	135	44	0	2	29	70	49	31	5
4	89	97	1	831	1047	76	60	27	14
5	27	134	69	1110	58745	11495	320	73	34
6	7	45	89	134	11681	119737	20118	696	190
7	0	5	21	30	333	20349	83837	9301	589
8	0	1	1	7	44	717	9417	15045	1495
9	0	0	0	0	18	171	610	1529	12605
10									
11									

Fig.26. GLCM of DR eye

The yields of classifiers have been tried and confirmed utilizing the learning application in MatLab and the dissipate plot acquired is as appeared in figure.27 , and furthermore the region under the bend fit is seen as appeared in figure.28. It is utilized in the characterization investigation so as to figure out which of the pre-owned models foresee the classes best.

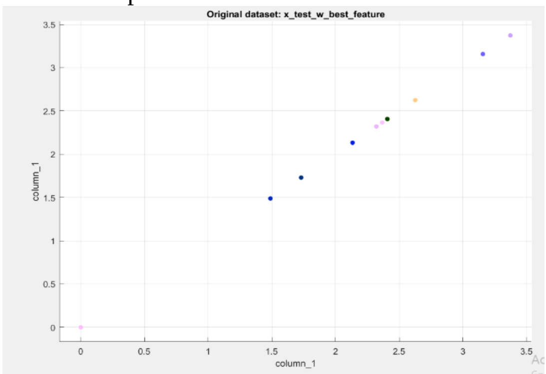

Figure.27 Scatter Plot for data set

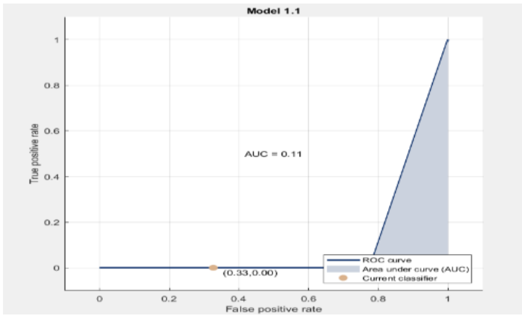

Figure.28. Area under Curve fit

The input images pixel values of the eye have been used to plot the mesh plot, stem plot for both normal eye and the DR eye. The mesh plot for normal eye is shown in figure 28 and the mesh plot for normal is as shown in figure 29.

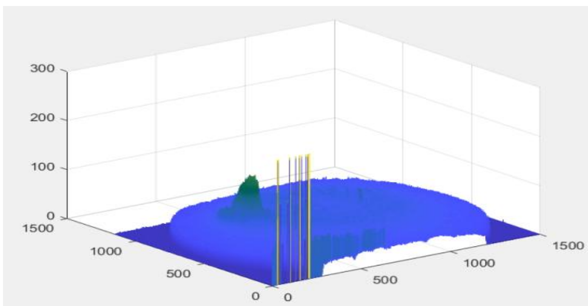

Figure.28 Mesh Plot for Normal eye

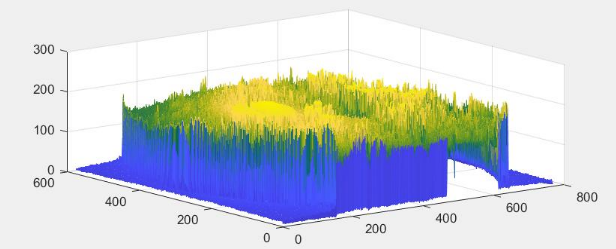

Figure.29 Mesh Plot for DR eye

The stem plot for both the normal and DR eye is as shown in figure 30 and 31 respectively.

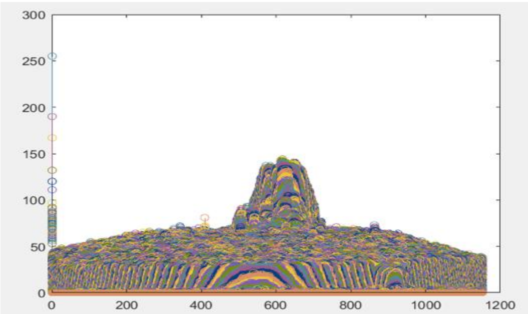

Figure.30 Stem Plot for Normal eye

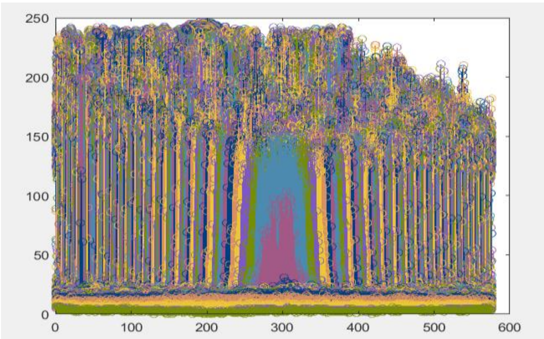

Figure.31 Stem Plot for DR eye

VI. CONCLUSION AND FUTUR WORK

A. Conclusion

Diabetic retinopathy is curable, if detected earlier. Exudates are easily detectable in the earliest of stages, i.e. in proliferative diabetic retinopathy. Major steps in detection of exudates are: Optic Disk elimination, Blood Vessel, and Detection of exudates. Optic disk is detected using Hough transform, hypot() is used to create a circle of radius 30 units around the centre co-ordinates obtained using Hough transform.

Blood Vessels are extracted using Canny edge detector, dilation helps to fill up the edges, erosion helps to fill the circles and then manual segmentation is applied to obtain the blood vessels. Hue channel of HSV plane is extracted, imtophat() is applied to green channel, optic disk and blood vessels are masked, and manual segmentation is applied to both the images to obtain the resultant image with hard exudates. The classifiers like Bayes classifier, Bagged Decision Tree classifier and the Support Vector Machine are implemented and the factors like error and accuracy with confusion matrix are generated. The results shows that the Support Vector machine is a best classifier compared with Naïve Bayes classifier and the Bagged Decision Tree with a accuracy of 96%.

Future scope

- The work can be extended to detect the soft exudates and micro-aneurysms, and to differentiate among the hard and soft exudates.
- In order to achieve portability and accessibility for user by creating a app based on the user input data.
- Also to carry-out the development of classifier to classify the eye as mild, moderate and severe diabetic retinopathy.
- And to implement it on the FPGA kits is to prove the role of System Generator in designing a hardware system for the recognition of Retinal exudates and thus identify the abnormalities present in retina.

ACRONYMS

DR: Diabetic Retinopathy
RGB: Reed Green Blue
AMD: Age related Macular Degeneration
SVM: Support Vector Machine
GLCM: Grey Level Co-occurrence Matrix
NDPR: Non- Proliferative Diabetic Retinopathy
PDR: Proliferative Diabetic Retinopathy
ECOC: Error Correcting Output Coding
GUI: Graphical User Interface
ROC: Receiver Output Characteristics
AUC: Area Under Curve

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