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Detection of Glaucoma from Retinal Fundus Images using Digital Image Processing

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Abstract: Glaucoma is a disease in which the optic nerve of the eye gets destroyed. As a result, it causes vision loss or blindness. However, with earlier diagnosis and treatment, eyes can be protected against severe vision loss. Most of times peripheral vision can be damaged earlier than an individual's central vision by Glaucoma because it does not show any sign and symptoms. The existing procedures to detect Glaucoma are time consuming and uncertain at the clinic. We propose a low cost Glaucoma detection system which is a computer-based technology and therefore, it uses algorithms to instantaneously detect and classify healthy and Glaucoma eye. It does this by analysing Region of Interest (ROI) of images through implementation of various image extraction features like Colour histogram, Haralick texture features using GLCM matrix, Multi level wavelet based feature using discrete wavelet transform. For Classification of healthy and Glaucoma eye we proposed Supervised Machine Learning approach using Random forest algorithm. The performance of the proposed method was evaluated in terms of accuracy, specificity, sensitivity and more parameters. From the experimental results of the proposed system, the accuracy, specificity, sensitivity is obtained as 95.65, 96.66 and 95.16 respectively.

Keywords: Glaucoma, GLCM matrix, Wavelet, Random Forest.

I. INTRODUCTION

Glaucoma often causes permanent blindness slowly without symptoms and warnings. It is a primary cause of vision loss worldwide. It is the group of the disease that contaminates the optic nerve and the optic nerve cells which results in loss of vision. In healthy eyes, there is normal balance between the fluids, one that is produced in the eye, and the second that leaves the eye through eye's drainage system. This balance of fluids keeps Inter Ocular Pressure (IOP) within the eye constant but in glaucoma, the balance of fluids produced within the eye is not maintained properly which in turn causes an increase in IOP, resulting in the damage of optic nerve. Due to increase in IOP, the cup size begins to increase which consequently increases the Cup to Disc Ratio. As For normal disc the CDR is considered to be less than 0.5 but in case of glaucoma, it is greater than 0.5. As the cup size increases it also affects the Neuro retinal Rim (NRR). NRR is the region located between the edge of the disc and the physiological cup. In the presence of glaucoma, area ratio covered by NRR in superior and inferior region becomes thin as compared to area covered by NRR in nasal and temporal region.

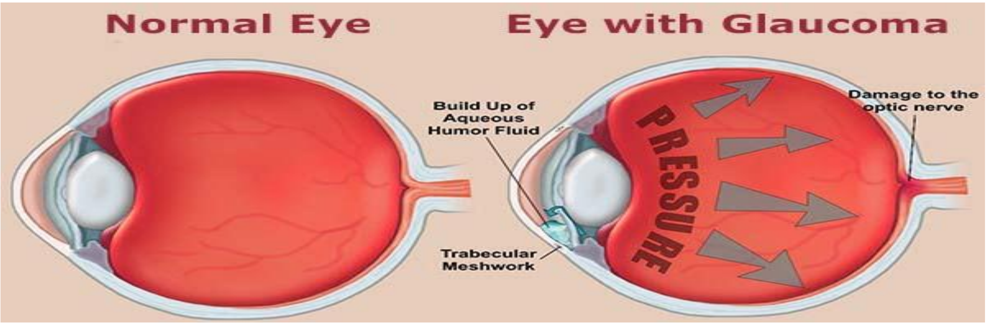

Fig. 1 Healthy and Glaucoma Eye

As detection of Glaucoma at later stage may lead to permanent loss of vision and person become blind for all his remaining lifetime. Figure 1 shows the healthy and Glaucoma eye structure. In Glaucoma optic nerve gets damaged as shown in seen in above figure than normal healthy eye. So early detect Glaucoma can prevents vision loss. To detect Glaucoma in early stage expert persons are required and these persons are not easily available in rural areas like developing countries like India. There is also possibility of human mistakes while manually operating devices which measures eye images. So need to develop automated system which will detect Glaucoma with more accuracy.

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II. LITERATURE REVIEW

Several studies and researches have been done in the last few years for the detection and classification of glaucoma. Following are the some researches and studies to detect glaucoma.

Bhupendra Singh Kirar, Dheeraj Kumar Agrawal[1] proposed hybrid and concatenation approach to increase the accuracy for measuring features of images. DWT decomposes images into approximate and detail coefficients and EWT decomposes images into its sub band images. The concatenation approach employs the combination of all features obtained using DWT and EWT and their combination. Extracted features from each of DWT, EWT, DWTEWT and EWTDWT are concatenated. Concatenated features are normalised, ranked and fed to singular value decomposition to find robust features.

Deepthi K Prasad, L.Vibha [2] proposed system concentrates on both Cup-to Disk Ratio (CDR) and different features to improve the accuracy of glaucoma. Morphological Hough Transform Algorithm (MHTA) is designed for optic disc segmentation. Intensity based elliptic curve method is used for separation of optic cup effectively. Further feature extraction and CDR value can be estimated. Finally, classification is performed with combination of Naive Bayes Classifier and K Nearest Neighbour (KNN).

E.Deepika, Dr.S.Maheswari [3] proposed an effective algorithm for the detection of glaucoma has been proposed. It consists of two main process, CDR detection and blood vessel segmentation. The entire process to detect abnormalities is split into several sections are arranged as follows: four pre-processing methods namely median filter, wiener filter, green channel extraction and CLAHE. Active contour model and morphological operation based candidate extraction is presented. This multiple number of pre-processing and candidate extraction creates diversity among the members.

Divya L., Jaison Jacob [4] proposed a modified decision making approach using bit-wise OR operation at the output of the classifier for different color components. The R, G, B and grey scale values are extracted from the input image. This is then subject to 2D EWT to form the sub-band images. Features are classified using Least Squares Support Vector Machine (LS-SVM) to classify between normal and glaucoma images. For performance analysis, the impact of testing and training on the detection and performance analysis of the classifier was done.

Namita Sengar, Malay Kishore Dutta et.al.[5] proposed the optic disc and hemorrhages are segmented in a particular region automatically by using adaptive thresholding and some geometrical features. In existing methods, the majority of work is based on diagnosis of glaucoma, but rarely on suspected glaucoma. So, the proposed method can helpful to diagnose the cases of suspected glaucoma.

Kavya N., Dr. Padmaja K.V.[6] proposed The method in which region of interest is extracted from the fundus image by using Hough Transformation. It is an automated way of segmentation used to obtain the accurate results and it replaces the manual segmentation. The k-mean clustering also used for segmentation which is another approach. From the segmented ONH, the different features like Gray Level Cooccurrence Matrix (GLCM) and Markov Random Field (MRF) are extracted.

Andres Diaz, Sandra Morales et.al.[8] proposed an automatic glaucoma diagnosis algorithm based on retinal fundus image is presented. This algorithm uses anatomical characteristics such as the position of the vessels and the cup within the optic nerve. Using several color spaces and the Stochastic Watershed transformation, different characteristics of the optic nerve were analyzed in order to distinguish between a normal and a glaucomatous fundus.

Atheesan S., Yashothara S.[10] proposed method which has the added advantage if being affordable. Here glaucoma is identified through cup (optical disc’s inner circle) to disc (outer circle) ratio (CDR) calculation and by the orientation of the blood vessels. Then contours are found, which in turn are used to draw the best fitting circle, thus finding the radius of cup and disc. After calculating CDR, the abnormal image can be recognized if CDR exceeds the threshold value. Otherwise it is a normal image. The system extracts the blood vessels and through their orientation glaucoma is identified.

III. PROPOSED WORK

As we know detection of glaucoma in early stage will avoid vision loss. Proposed a low-cost Glaucoma detection system which is a computer-based technology and therefore, it uses algorithms to instantaneously detect and classify healthy and Glaucoma eye. Implemented machine learning approach using Random Forest Algorithm for higher accuracy.

System block diagram is as shown in above figure 2. It consists of training and testing model. Training model consist of all necessary operations Pre-processing, ROI extraction, feature extraction, model training, and trained model. Input image is selected from the database. Database consist of healthy and glaucoma fundus images. In pre-processing block, images are pre-processed. The color fundus images are resized to 256 × 256 which increases the processing speed. In ROI extraction, Region of Interest (ROI) is extracted by applying Morphological operations. In feature extraction features are extracted from ROI retinal fundus image such as color histogram features, Haralick texture features are used to obtain features from input ROI image. Model is trained and saved using random forest classifier.

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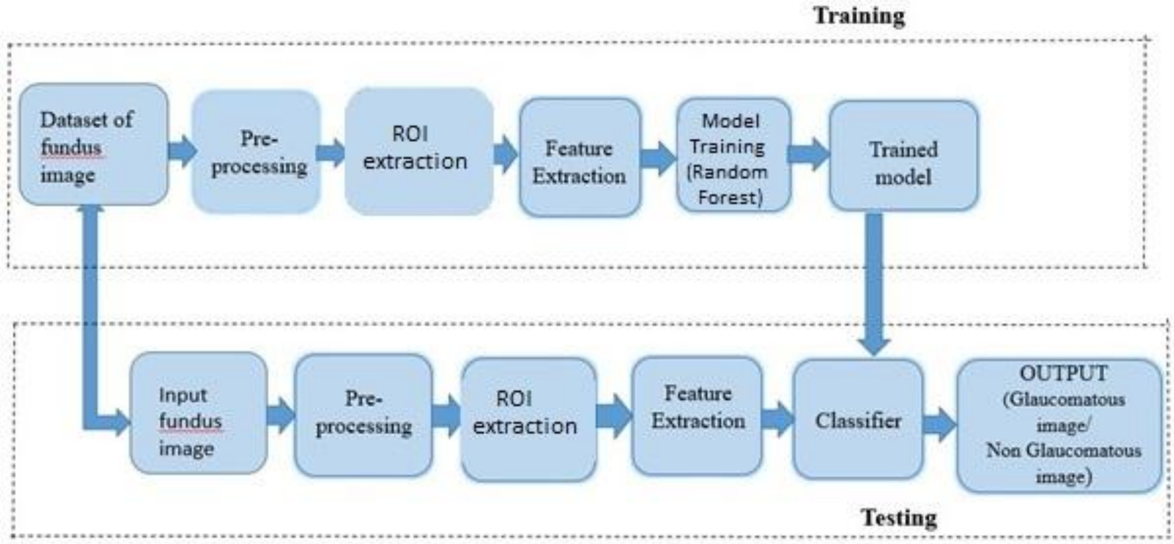

Fig. 2 Block Diagram of Proposed System

Testing model consist of all necessary operations Pre-processing, ROI extraction, feature extraction, classifier. The functions of Pre-processing, ROI extraction, feature extraction are as above. Using trained Random forest model classifier retinal fundus images are classified as Glaucomatous and Normal that is Non Glaucomatous. The details of blocks are given below.

A. Input / database Image

In Image Acquisition step the input image is selected from the database. Typical healthy and glaucoma fundus images are shown in figure 3.2. This paper has used (healthy and glaucomas) fundus images of from following three database. Drishti-GS1 [18] dataset consists of a total of 101 images. All images were collected at Aravind eye hospital, Madurai from visitors to the hospital. High-Resolution Fundus (HRF) Image Database [19] consists of 30 images. DRIONS Digital Retinal Images for Optic Nerve Segmentation [20] Database consist of 110 colour digital retinal images.

B. Pre-processing

Pre-processing is an important part of digital image processing. Glaucoma and healthy images are pre-processed. The color fundus images are resized to 256 × 256 to make images of the same resolution. Image resizing increases the processing speed. Resized images are converted from RGB to its red, green and blue components. In the proposed method only green image component is used because it contains more information. Green image components are subjected to contrast adjustment for increasing the dynamic range, appearance and contrast of images.

C. ROI extraction

Main objective for ROI extraction is to extract Region of Interest (ROI). In Image processing, morphological operations are the one that processes an image by applying a structuring element of a particular type and shape on the input image acting as a mode for comparison. Operation includes dilation, erosion, opening and closing.

D. Feature Extraction

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is so computed that it quantifies some significant characteristics of the object.
In this project we have selected the following features to extract the features from ROI retinal fundus image.

1 Colour histogram
2 Haralick texture features
3 Multi level Wavelet based features

1. Colour histogram

Color histograms are defined as a set of bins where each bin denotes the probability of pixels in the image being of a particular color. A color histogram for a given image is defined as a vector:
$H = \{H[0], H[1], H[2],\ldots, H[i],\ldots, H[N]\}$
where i represents a color in the color histogram and corresponds to a sub cube in the RGB color space, $H[i]$ is the number of pixels in color i in that image, and N is the number of bins in the color histogram, i.e., the number of colors in the adopted color model.

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2. Haralick based texture features

Haralick et al. introduced Gray Level Co occurrence Matrix (GLCM) and texture features back in 1973. It consists of two steps for feature extraction. The GLCM is computed in the first step, while the texture features based on the GLCM are calculated in the second step. GLCM shows how often each gray level occurs at a pixel located at a fixed geometric position relative to each other pixel, as a function of the gray level. From GLCM matrix following texture features is calculated.

Parameter	Formula
Contrast	$\sum_{n=0}^{N_g-1} n^2 \sum_{\|i-j\|=n} P_d\ (i,j)$
Correlation	$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-\mu_i)P_d(i,j)}{\sigma_i\sigma_j}$
Homogeneity	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P_d(i,j)}{1+\|i-j\|}$
Energy	$\sum_{i=1}^{N_g}\sum_{i=1}^{N_g} P_d^2(i,j)$

3. Multilevel Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) of a signal is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

The signal is also decomposed simultaneously using a high pass filter h. The outputs giving the detail coefficients from the high pass filter and approximation coefficients from the low pass. It is important that the two filters are related to each other and they are known as a quadrature mirror filter. Following features are calculated.

Parameter	Formula
Mean	µ
Standard Deviation (SD)	$\sqrt{E(x-\mu)^{\wedge}2}$
RMS	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}\|X_n\|^2}$
Entropy (E)	-sum (P.*log2(P))
Smoothing Index(smi)	$1-\frac{1}{(1+\sigma^2)}$
Skewness	$\frac{(X-\mu)^3}{\Sigma}$
Kurtosis	$n\frac{\sum_{i=1}^{n}(Xi-Xavg)}{(\sum_{i=1}^{n}(Xi-Xavg)^2)^2}-3$

E. Classification

For classification used Random forest algorithm which is a supervised machine learning algorithm. When the training set for the current tree is drawn by sampling with replacement, about one-third of the cases are left out of the sample. This oob (out-of-bag) data is used to get a running unbiased estimate of the classification error as trees are added to the forest. It is also used to get estimates of variable importance. After each tree is built, all of the data are run down the tree, and proximities are computed for each pair of cases. If two cases occupy the same terminal node, their proximity is increased by one. At the end of the run, the proximities are normalized by dividing by the number of trees. Proximities are used in replacing missing data, locating outliers, and producing illuminating low-dimensional views of the data.

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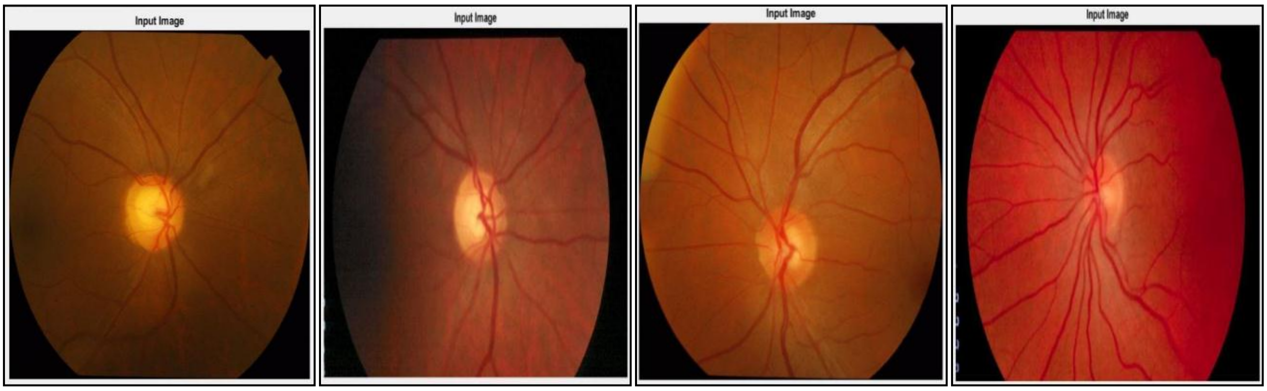
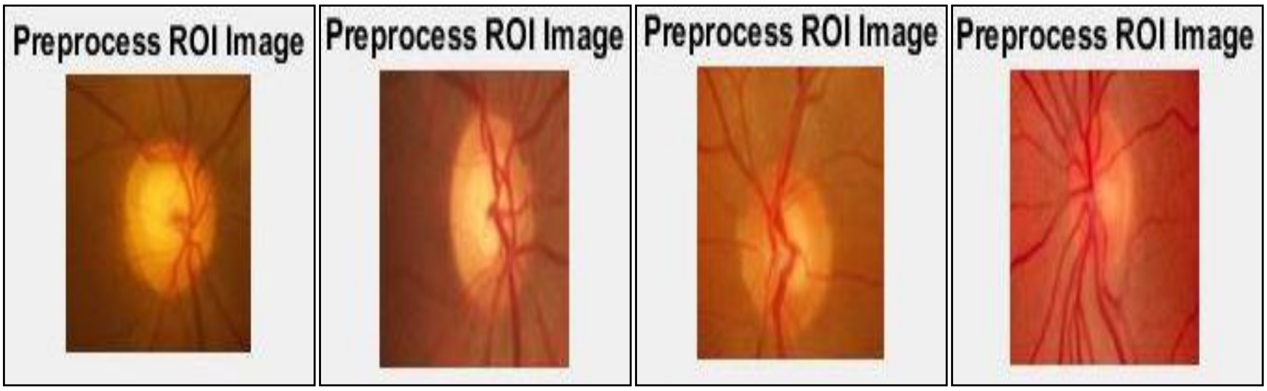
IV. RESULTS AND DISCUSSIONS

Our database contains three databases as Drishti-GS1 [18], High-Resolution Fundus (HRF) Image Database [19] and DRIONS Digital Retinal Images for Optic Nerve Segmentation [20] database which contains about 161 retinal fundus images. Out of 161 images 69 images are used for learning or training purpose and 92 images are used for testing purpose. The proposed technique has been implemented using MATLAB version R2015a environment and implemented using Intel core i3-6006U processor speed at 2.00 GHz with 4 GB RAM.



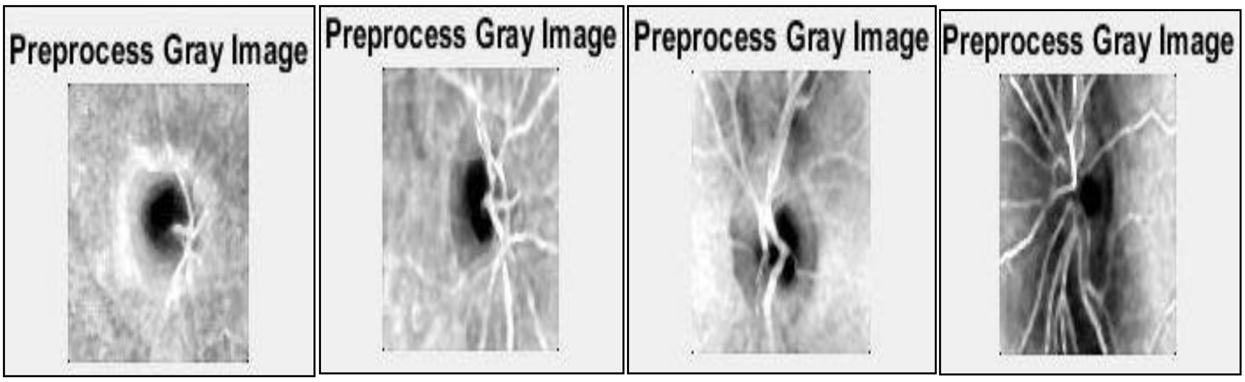
a b c d

Fig. 4 Test images, a) and b) Glaucoma Images c) and d) Normal Images



a b c d

Fig. 5 Pre process ROI images, a) and b) Glaucoma Images c) and d) Normal Images



a b c d

Fig. 6 Pre process gray images, a) and b) Glaucoma Images c) and d) Normal Images

As shown in above figures 4, 5 and 6, we obtained original input image, Pre process ROI and Pre process gray images for Glaucoma and Normal cases respectively.

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A. Confusion Matrix:

A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The confusion matrix is a two by two table that contains four outcomes produced by a binary classifier.

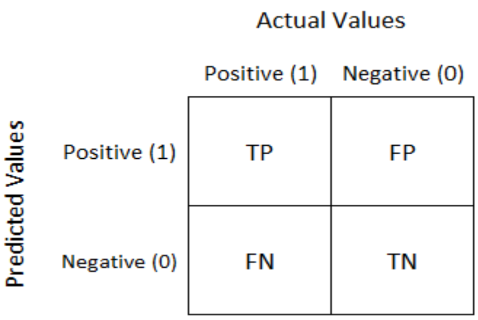

Fig. 7 Confusion Matrix

- True positive (TP): correct positive prediction
- False positive (FP): incorrect positive prediction
- True negative (TN): correct negative prediction
- False negative (FN): incorrect negative prediction

Following performance parameters were calculated from confusion matrix as follows.

Parameter	Formula
Accuracy	$\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FN}+\mathrm{FP}}$
Error rate (ERR)	$\frac{\mathrm{FP}+\mathrm{FN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FN}+\mathrm{FP}}$
Sensitivity (Recall or True Positive Rate)	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$
Specificity (True Negative Rate)	$\frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}}$
Precision (PPR)	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$
F-score or F-measure	$2 * \frac{\mathrm{PPR} * \mathrm{recall}}{\mathrm{PPR}+\mathrm{recall}}$
Negative Predictive Rate (NPR)	$\frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FN}}$
False Negative Rate (FNR)	$\frac{\mathrm{FN}}{\mathrm{TP}+\mathrm{FN}}$
False Positive Rate (FPR)	$\frac{\mathrm{FP}}{\mathrm{TN}+\mathrm{FP}}$
Rate of Negative Predictions (RNP)	$\frac{\mathrm{TN}+\mathrm{FN}}{\mathrm{P}+\mathrm{N}}$
Rate of Positive Predictions (RPP)	$\frac{\mathrm{TP}+\mathrm{FP}}{\mathrm{P}+\mathrm{N}}$
Matthews Correlation Coefficient (MCC)	$\frac{\mathrm{TP\ X\ TN}-\mathrm{FN\ X\ FP}}{\sqrt{(\mathrm{TP}+\mathrm{FN})(\mathrm{TP}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})}}$

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B. Confusion Matrix for Training and Testing

a b

Fig. 8 Confusion matrix for a) Training b) Testing

As shown in figure 8 a) obtained the trained model by using 69 retinal fundus images. The accuracy of trained model is validated as 100 percentages. In figure 8 b) testing is done on 92 retinal fundus images and accuracy obtained is 95.7 percentages

C. Comparative Performance Parameters

Table 1 Comparative performance parameter

Parameter	**Ref [1]**	**Ref [10]**	**Proposed**
Accuracy	88.73	-	95.65
Sensitivity	85.36	97	95.16
Specificity	92.14	82	96.66
F-Score	-	96	97.68
Positive Predictive Rate	92.36	95	98.33
Negative Predictive Rate	87.88	-	90.63
False Negative Rate	14.64	-	4.84
False Positive Rate	7.86	-	3.33
Rate of Negative Prediction	53.25	-	34.78
Rate of Positive Prediction	46.75	-	65.22
Matthews Correlation Coefficient	78.76	-	90.38

V. CONCLUSIONS AND FUTURE SCOPE

Glaucoma is a disease in which the optic nerve of the eye gets destroyed. As a result, it causes vision loss or blindness. However, with earlier diagnosis and treatment, eyes can be protected against severe vision loss. In this paper, we propose a low cost computer based technology to classify healthy and Glaucoma eye. It does this by analyzing region of interest (ROI) of images through implementation of various image extraction features like Colour histogram, Haralick texture features using GLCM matrix, Multi level wavelet based feature using discrete wavelet transform. For Classification we proposed Supervised Machine Learning approach using Random forest algorithm. The performance of proposed system

is measured in terms of accuracy, specificity, sensitivity as 95.65, 96.66 and 95.16 respectively which are better than earlier detection techniques.
As the field of interest and the results of this study turned out to be rich and broad, there are several ways to extend it. Some of the possible ways to investigate this work in the near future are discussed below.

1. This project can be extended with Deep Learning features.
2. Design a database connected with the software to save the patients fundus images and medical reports.

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