International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 09 | Sep 2020 www.irjet.net p-ISSN: 2395-0072

Glaucoma Disease Detection by using Tree Bagging Algorithm in Fundus Images of Eye

Payal N. Rabade[1], Radhika Harne[2]

[1]M.Tech Student, Department of Electronics Engineering, Government College of Engineering Amravati, Maharashtra, India.
[2]Assistant Professor, Department of Electronics Engineering, Government College of Engineering Amravati, Maharashtra, India.

Abstract - *Glaucoma is the second leading cause of blindness across the world. It is an eye disease in which Intra-ocular Pressure (IOP) in the eye increases continuously, that affects the optic nerve of eye which carries signals to the eye. This disease can leads to permanent blindness if not treated at earlier stage. In this paper, we present a novel method based on feature extraction and bootstrap aggregating, also called tree bagging to detect Glaucoma and classify normal eye and glaucomatous eye patient. Bagging is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy, used in statistical classification. Wavelet based texture feature and statistical features are used for detection of glaucoma from fundus images. Tree Bagger classifiers is used for classification of normal eye patient and patient having Glaucoma. Classification accuracy of tree Bagger classifier is 96.1% for fundus image of different patient. Processing time of tree bagger classifier for testing dataset is 16.40s.*

Key Words: Glaucoma, Intra ocular pressure(IOP), Optic nerve, Fundus image, Tree bagger classifier.

1. INTRODUCTION

Glaucoma comes second after diabetic retinopathy in eye diseases which causes blindness. Glaucoma is a eye disease that damages the optic nerve in the eye that carries the images that we see to our brain. In healthy eye, a transparent liquid called the aqueous humor circulates inside the front portion of the eye to maintain a constant healthy eye pressure. The eye continuously produces a small amount of aqueous humor, an equal amount of this liquid flows out of the eye through a microscopic drain which is known as a trabecular meshwork in the drainage angle. In case of glaucoma patients the aqueous humor does not flow through the drainage angle properly causing fluid pressure called as intraocular pressure (IOP) in the eye to increase, and this pressure causes damage to the optic nerve fibers. These damaged nerve fibers leads to patches of vision loss, and if not treated at early stage it may lead to total blindness. Symptoms also appear gradually, starting with preferable vision loss, which may go unnoticed until the central vision is affected. Fundus images are obtained from fundoscopy, which is one of the modern medical imaging techniques that helps ophthalmologists to identify structural changes in the optic disc to detect Glaucoma. In India, at least 12 million people affected by Glaucoma and nearly 1.2 million people blind from the disease. Glaucoma prevalence increases with age. Image processing based approach for analyzing fundus images for diagnosis of glaucoma is an emerging area of research and some work has been reported in this area.

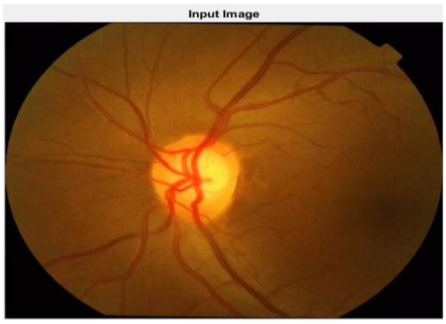

Fig -1: Input Fundus Image from Drishti-GS1 dataset.

Progression of glaucoma occurs due to an increase in intraocular pressure and results in the damage of optic nerve. Progression of glaucoma can be stopped if detected at an early stage. There are no early symptoms in patients having glaucoma and the only way to detect glaucoma at an early stage is the structural change that occurs in the internal eye. Most Glaucoma cases happen without signs and symptoms because peripheral vision can be damaged before an individual's central vision is affected [4]. Fundoscopy and Optical Coherence Tomography (OCT) are two modern medical imaging techniques which enables the ophthalmologists to analyze the internal structural retinal details. Fundoscopy is a technique which reveals the internal fundus details[11]. In glaucoma detection, Fundoscopy helps to examine optic nerve, optic cup and optic disc as it is cost effective as compare to Optical coherence tomography, So in our research we have used fundus images. Glaucoma is not curable, so early diagnosis is the only possible way to prevent loss of vision. Computer aided diagnosis system may help screening the disease [2].

2. LITERATURE SURVEY

Juan Carrillo, Lola Bautista et al.[1] gives computational tool for automatic glaucoma detection from fundus image of the eye. The disc segmentation was done by thresholding, the vessel segmentation was done using edge detection, and for the cup segmentation it was presented a method that uses the vessels and the cup intensities, after which CDR ratio is calculated. The absolute error was 8.6% and the relative error was 19.2%. Atheesan S., Yashothara S.[5] proposed automatic system to identify Glaucoma through cup to disc ratio (CDR) calculation and by the orientation of the blood vessels. In this system, cup and disc are extracted using average and maximum grey level pixels respectively with the use of histogram. Then contours are used to draw the best fitting circle, to find the radius of cup and disc. After calculating CDR, if CDR exceeds the threshold value then it is abnormal image, otherwise it is a normal image. They have proved that if the CDR value is between 0.0 and 0.3, then image is normal and if it is greater than 0.3, then it is glaucomatous. Blood vessel orientation is recognized by the distribution of the extracted blood vessels in four equal quarter circles. Ayushi Agarwal, Shradha Gulia et. al, [6] proposed an efficient method to analyze a computer-aided fundus image which can act as a diagnostic tool for detection of glaucoma. The optic disk and optic cup are automatically localized from digital fundus images using image adaptive thresholding technique. Statistical features such as mean and standard deviation are considered and analyzed with respect to image histogram to track the threshold value that depends upon a relationship between the statistical features. Based on these threshold values, optic disk and optic cup are detected, after which CDR is calculated. Total number of white pixels is calculated individually for segmented optic disk and optic cup image and further cup to disc ratio is obtained. If CDR is greater than or equal to 0.3 then image is classified as glaucomatous else image is glaucoma free. Malay Kishore Dutta, Amit Kumar Mourya et al [7] proposed an automated image processing approach for detection of glaucoma which may be a diagnostic tool for detection of glaucoma suspects. This method is based on the segmentation of optic disk and the optic cup and calculate the cup-to-disc ratio. A double threshold method is used for segmentation of optic cup and optic disk first for removing the blood vessels and background and second threshold for segmentation of the super intensity pixels in the OD and OC. Hough Transform is used to measure the radius of optic disk and optic cup. The vertical cup to disk ratio is used as a parameter for detection of glaucoma in the fundus image. According to this method, if the CDR is more than 0.75 then the patient is having Glaucoma disorder. If the ratio is less than the 0.75 then it is a normal eye. NM Noor, NEA Khalid et al [8] proposed a method for glaucoma detection using digital fundus images with color multi-thresholding segmentation. This work based on segmentation of optic cup and optic disc using color multi-thresholding segmentation and extract feature such as cup to disc (c/d) ratio. Color multi-thresholding can provide assistance for the measurement of CDR for Glaucoma detection.

3. METHODOLOGY

The block diagram of proposed methodology is shown in Fig. 2. Machine Learning approach works in two phases first is training and second is testing. So before testing, training has to be done, also the training should be 100%, then the testing could be better. So the proposed methodology is divided into phases, which is training and testing of input fundus image.

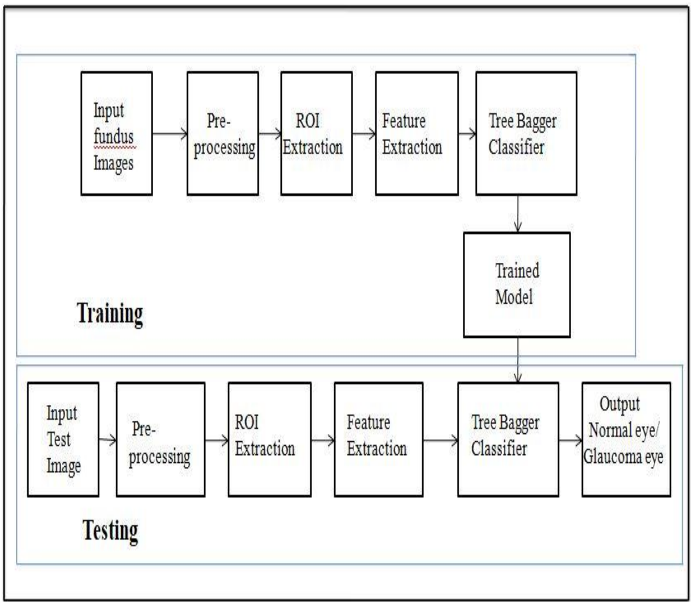

Fig-2: Block diagram of proposed method.

3.1Preprocessing of fundus images

The purpose of the pre-processing step is to produce data which are compatible with the Glaucoma detection and classification system. Preprocessing mainly focus on the general operations consisting of image resize, gray scale conversion, image filtering, contrast adjustment, image binarization and mor- phological operations, the center of optic disc region is calculated to extract the region of interest.

3.2 ROI Extraction

Some morphological operation is performed on pre-processed input image, after that centroid is calculated to find the center of the optic disc region. After that 100 pixel are added and subtracted from row centre and column centre of input image and image is cropped into square shape to get the ROI of the input image. Gray scale conversion operation performed on ROI image which is followed by Median filtering operation which remove noise from the image. Image enhancement operation is performed by adjusting the low and high intensities of image also increases the contrast of the image.

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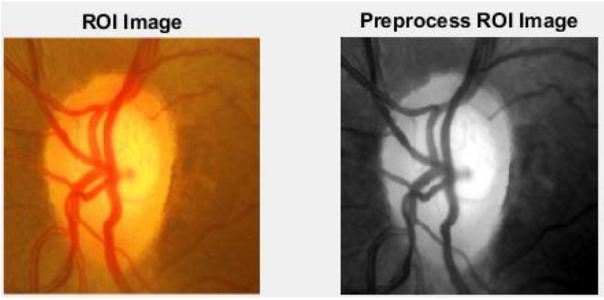

Fig-3: a)ROI Image of input fundus image b) Pre processed ROI image of input fundus image

3.3 Feature Extraction

Feature extraction is the process where important information, namely feature vectors, from the fundus images are created. It is one of many factors which are used to increase the effectiveness of a detection system. Feature extraction can play a significant factor for obtaining high accuracy in Glaucoma detection and classification system, especially if there is a lot of training data available. It is a process that extracts the significant information from the fundus image and transforms them into feature vector data. Features are significant facts (i.e. feature vectors) about the fundus images, which are utilized to train a classifier.

3.3.1Wavelet based texture features

Discrete wavelet transform (DWT) represents an image as a subset of wavelet functions using different locations and scales. It makes some decomposition images. According to the characteristic of the DW decomposition, an image can be decomposed to four sub-band images through a 1-level 2-D DWT. This 2D-DWT causes a decomposition of approximation coefficient in four component ,the approximation component, and the detail component in three orientation which is horizontal, vertical, and diagonal .

3.3.2Principal Component Analysis (PCA)

PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. Reducing the number of variables of a data set naturally affects on accuracy, but the trick in dimensionality reduction is to deal a little accuracy for simplicity. Because smaller data sets are easier to discover and visualize and make analyzing data easier and faster for machine learning algorithms without irrelevant variables to process. The idea of PCA is simple, reduce the number of variables of a data set, while preserving as much information as possible.

3.3.3Texture Features Extraction

Texture analysis is a quantitative method that can be used to quantify and detect structural abnormalities in different tissues. The purpose of feature extraction is to reduce original data set by measuring certain features that distinguish one region of interest from another. The analysis and characterization of textures present in the fundus images of eye can be done by using the features extracted from GLCM. Haralick texture features are calculated from a Gray Level Co-occurrence Matrix, (GLCM), a matrix that counts the co-occurrence of neighboring gray levels in the image. The GLCM is a square matrix that has the dimension of the number of gray levels *N* in the region of interest (ROI). The Gray-Level Co-occurrence Matrix (GLCM) seems to be a well-known statistical technique for feature extraction. The GLCM is a tabulation of how often different combinations of pixel gray levels could occur in an image. The goal is to assign an unknown sample image to one of a set of known texture classes.

1. Contrast:

Gives the local variation in the gray level co-occurrence matrix .Contrast is 0 for a constant image.

$$\text{Contrast} = \sum_{i,j} |i-j|^2\, p(i,j)$$

2. Correlation:

Gives the joint probability occurrence of the particular pixel pair.

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j}$$

3. Energy:

Gives the sum of squared elements in the Grey level co-occurrence matrix Energy is 1 for a constant image.

$$\text{Energy} = \sum_{i,j} P(i,j)^2$$

4. Homogenity :

Gives the proximity of the distribution of element in the grey level co-occurrence matrix to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM.

$$\text{Homogenity} = \sum_i \sum_j \frac{1}{1+(i,j)^2} p(i,j)$$

3.3.4 Hu Moments

Hu moment (or rather Hu moment invariants) are a set of 7 numbers calculated using central moments that are invariant to image transformations. The first 6 moments have been proved to be invariant to translation, scale, and rotation, and reflection. While the 7th moment's sign changes for image reflection.

3.3.5 Statistical Feature

Statistical features extracted here are mean, variance, standard deviation, smoothing index, skewness, kurtosis, entropy. Table.1 below gives the formulae for statistical features.

	Statistical Features	Formula
1.	Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} I$
2.	Variance	$\sigma = E(x - \mu)^2$
3.	Standard Deviation	$SD = \sqrt{E(x - \mu)^2}$
4.	Smoothing Index	$Smi = 1 - \frac{1}{(1+\sigma^2)}$
5.	Skewness	$Skewness = \frac{(X-\mu)^3}{\Sigma}$
6.	Kurtosis	$K = n\frac{\sum_{i=1}^{n}(X_i - X_{avg})}{(\sum_{i=1}^{n}(X_i - X_{avg})^2)^2} - 3$
7.	Entropy	$S = \sum_{i=0}^{n=1} p_i \log_2 p_i$

Table-1: Statistical features with formulae.

3.3.6 Color moment

Color moments are measures that characterized color distribution in an image. Color moments are mainly used for color indexing purposes as features in image retrieval applications in order to compare how similar two images are based on color. Usually one image is compared to a database of digital images with pre-computed features in order to find and retrieve a similar Image. Each comparison between images results in a similarity score, and the lower this score is the more identical the two images are supposed to be. It is usually the case that only the first three color moments are used as features in image retrieval applications as most of the color distribution information is contained in the low-order moments. Since color moments encode both shape and color information they are a good feature to use under changing lighting conditions. Color moments can be calculated for any color model. Three color moments are computed per channel (e.g. 9 moments if the color model is RGB).

1. **Mean**

The first color moment can be explained as the average color in the image, and it can be given as ,

$$E_i = \sum_{j=1}^{N} \frac{1}{N} P_{ij}$$

where N is the number of pixels in the image and p_{ij} is the value of the j-th pixel of the image at the i-th color channel.

2. **Standard Deviation**

The second color moment is the standard deviation calculated by taking the square root of the variance of the color distribution.

$$\sigma_i = \sqrt{(\frac{1}{N}\sum_{j=1}^{N}(p_{ij} - E_i)^2)}$$

Where,

$E_i E_i$ is the mean value, for the i- th color channel of image

3. **Skewness**

The third color moment is the skewness. It evaluate how asymmetric the color distribution is, so it gives information about the shape of the color distribution. It can be given as,

$$S_i = \sqrt[3]{(\frac{1}{N}\sum_{j=1}^{N}(p_{ij} - E_i)^3)}$$

3.4 Classification

An ensemble is itself a supervised learning algorithm, because it can be trained and then used to make predictions. Ensemble methods combine different decision trees classifiers to produce better predictive model than a single decision tree classifier. Bagging is a machine learning ensemble algorithm which improve the stability and accuracy of machine learning algorithm. It also reduces variance and helps to avoid over fitting. Although it is usually applied to decision tree method. Bagging is a combination of two ideas, bootstrap re-sampling and aggregation. It is a special case of the model averaging approach, which combines several decision trees to produce better predictive performance than utilizing a single decision tree. It creates several subsets of data from training sample chosen randomly with replacement known as bootstrap samples. Each bootstrap sample is used to train their decision trees. When making a prediction, each decision tree in the ensemble make its own prediction. Average of all the predictions from each decision trees are used to get the output which is more accurate than a single decision tree. The main principle behind this algorithm is that a group of weak learners come together to form a strong learner, thus increasing the accuracy of the model.

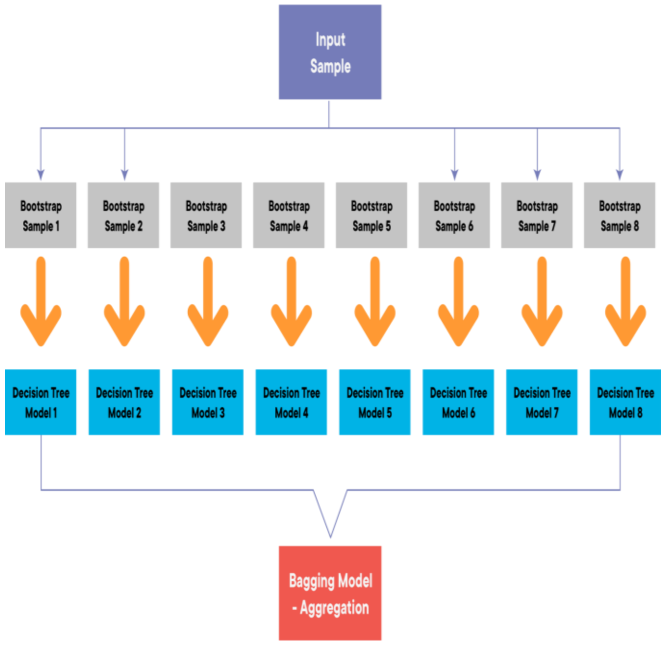

Fig-4: Flow of Tree Bagger Classifier.

4. DATASET

The database used in this work is Drishti-GS1, provided by Medical Image Processing (MIP) group, International Institute of Information Technology (IIIT) Hyderabad. Drishti-GS1 is a dataset meant for validation of segmenting OD, cup and detecting notching, which is available in PNG (portable network graphics files) format. The images in the Drishti-GS1 dataset have been collected and annotated by Aravind Eye hospital, Madurai, India. This dataset is of a single population as all subjects whose eye images are part of this dataset are Indians. The dataset is divided into two set, a training set and a testing set of images. Training images (50) are provided with ground truths for OD and cup segmentation and notching information. Drishti-GS1 dataset consists of a total of 101 images. These have been divided into 50 training and 51 testing images. Selected patients were between 40-80 years of age with roughly equal number of males and females. The images are in PNG format having very high resolution and size, so it is required to resize the image. So we convert the PNG format image to JPG image. JPGs are raster images that use lossy compression, so the converted files will be a smaller file size, but image quality remains the same.

5. RESULT AND DISCUSSION

Performance of the system is tested on 51 fundus images of different patients .Dataset consist of 50 training images 51 testing images. Initially Tree bagger classifier trained using training dataset of 50 images, having 25 images of normal and 25 image of Glaucoma patients. Tree bagger classifier gives the accuracy of 100% for the training dataset. The testing dataset consist of 51 images, the classifier tested on testing dataset and achieves the classification accuracy of 96.1%.All the performance parameters are analyzing using confusion matrix. The fig.5 shows that great accuracy is achieved using combination of wavelet based texture features, statistical features and color moment.

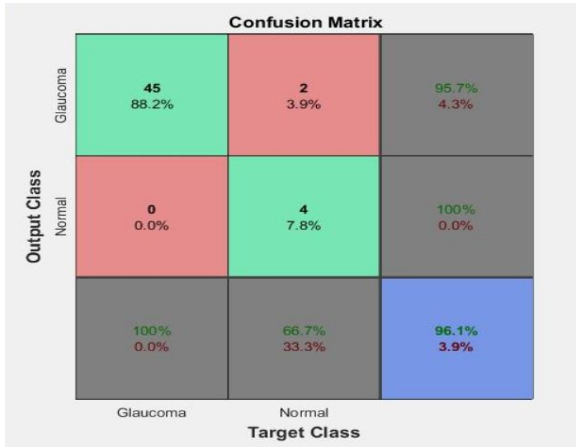

Fig-5: The confusion matrix of tree bagger classifier for testing dataset.

As shown in the confusion matrix, out of 6 normal image 4 images are correctly detected and 2 images are incorrectly detected. Hence an error rate of 3.9% has occurred. Accuracy of 96.1% is achieved by Tree Bagger classifier, also, specificity is 95.74%, sensitivity is 100%, F-score is 71.42. Fig.6 shows the out-of-bag(OOB) error rate of tree bagger classifier, which is for 20 trees.(OOB) error, also called out-of-bag estimate, is a method of measuring the prediction error of tree bagger classifier.

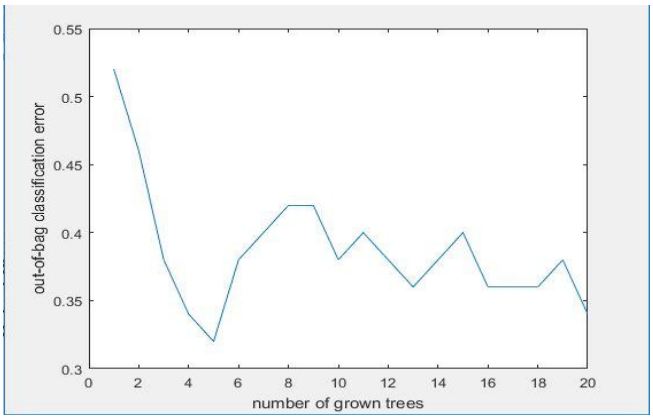

Fig-6: Out-of-Bag Error of tree bagger Classifier for 20 trees.

6. CONCLUSION

The present study demonstrates the effectiveness of different features and the Tree Bagger classifier algorithm for Glaucoma detection and classification. The tree bagger classifier achieves the classification accuracy of 96.1%. Wavelet based texture features, statistical features and color moment are the features utilized to detect Glaucoma and perform a vital role in the classification process. The processing time of the Tree Bagger classifier for training is 16.74 sec. and for testing is 16.40 sec. Deep learning architecture can be adopted in future for large dataset.

REFERENCES

[1]Juan Carrillo, Lola Bautista, Jorge Villamizar ,Juan Ruedaz, Mary Sanchez and Daniela rueda "Glaucoma detection using fundus image of the eye". XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA)2019.

[2] Namita Sengar, Malay Kishore Dutta, Radim Burget, Martin Ranjoha "Automated Detection of Suspected Glaucoma in Digital Fundus Images".40th International Conference on Telecommunications and Signal Processing (TSP)2017.

[3] J. Ayub, J. Ahmad, J. Muhammad, L. Aziz, S. Ayub, U. Akram, and I.Basit "Glaucoma detection through optic disc and cup segmentation using K-mean clustering".2016 International Conference on Computing, Electronic and Electrical Engineering (ICE Cube), pages 143–147, 2016.

[4] Mohammad Aloudat and Miad Faezipour "Determination for Glaucoma Disease Based on Red Area Percentage" 2016 IEEE Long Island Systems,Applications and Technology Conference (LISAT).

[5] Atheesan S., Yashothara S. "Automatic Glaucoma Detection by Using Funduscopic Images" 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET).

[6]Ayushi Agarwal, Shradha Gulia et al"Automatic Glaucoma Detection using Adaptive Threshold based Technique in Fundus Image" 2015 38th International Conference on Telecommunications and Signal Processing (TSP).

[7] Malay Kishore Dutta, Amit Kumar Mourya,et al "Glaucoma Detection by Segmenting the Super Pixels from Fundus Colour Retinal Images" 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom).

[8]NM Noor, NEA Khalid,et al,"Optic Cup and Disc Color Channel Multithresholding Segmentation" 2013 IEEE International Conference on Control System, Computing and Engineering, 29 Nov. - 1 Dec. 2013, Penang.

[9] F. Khan, S.A. Khan, U.U. Yasin, I. Haq, U. Qamar, "Detection of glaucoma using retinal fundus images", The 2013 IEEE Biomedical Engineering International conference (BMEi-CON 2013), pp. 1-5,October 2013.

[10] A.Murthi, M.Madheswaran "Enhancement Of Optic Cup To Disc Ratio Detection In Glaucoma Diagnosis" 2012 International Conference on Computer Communication and Informatics (ICCCI -2012), Jan. 10 – 12, 2012, Coimbatore, INDIA

[11] Anum Abdul Salam,M.Usman Akram1,etal, 'Autonomous Glaucoma Detection From Fundus Image Using Cup to Disc Ratio and Hybrid Features' 2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT).

[12] S.M. Nikam and C.Y. Patil. "Glaucoma detection from fundus images using matlab gui." In 2017 3rd International Conference on Advances in Computing, Communication & Automation (ICACCA)(Fall), pages 1–4, 2017.

[13] B. Naveen Kumar, R.P. Chauhan, Nidhi Dahiya "Detection of Glaucoma using Image processing techniques: A Review"2016 International Conference on Microelectronics, Computing and Communications(MicroCom).

[14]A Comprehensive Retinal Image Dataset for the Assessment of Glaucoma from the Optic Nerve Head Analysis. Sivaswamy J, S. R. Krishnadas, Arunava Chakravarty, Gopal Dutt Joshi, Ujjwal and Tabish Abbas Syed, JSM Biomedical Imaging Data Papers, 2(1):1004, 2015.

[15]Drishti-GS: Retinal Image Dataset for Optic Nerve Head(ONH) Segmentation. Sivaswamy J, Krishnadas K. R, Joshi G. D, Jain Madhulika, Ujjwal and Syed Abbas T., IEEE ISBI, Beijing

[16] Pavithra G. , Anushree G. et al, "Glaucoma Detection using IP Technique"2017International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS).

[17] Andres Diaz, Sandra Morales et al., "Glaucoma diagnosis by means of optic cup feature analysis in color fundus images" 2016 24th European Signal Processing Conference (EUSIPCO).