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A Novel approach for Glaucoma Disease Identification through Optic Nerve Head Feature Extraction and Random Tree Classification

J. Jeslin Shanthamalar [1] and R. Geetha Ramani [2]

[1,2]*Department of Information Science and Technology, Anna University, Chennai, India*

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Abstract: Glaucoma is one of the second leading causes of blindness behind cataracts and this sight-stealing disease affected 4.5 million people worldwide was estimated by World Health Organization. Glaucoma is a group of related eye disorders that cause extra fluid builds up in the front part of an eye leads to ocular hypertension can damage the optic nerves. The optic Nerve Head is a bundle of one million nerve fibers that carries visual signals from the eye to the brain. A novel approach is proposed for glaucoma identification by optic nerve head feature extraction from multi color channel using image processing followed by disease classification using data mining techniques. The proposed system uses combination of optic Disc localization, optic nerve head region segmentation, color space conversion, color channel selection, extracts gray level co-occurence matrix, histogram and statistical features of 29 color channels, feature relevance analysis and disease classification process. This system was tested on three publically available databases Drishti-GS1, RIM-ONE r1 and RIM-ONE r2 and also evaluated on ground truth given by experts achieves the overall positive predictive value of 97.96% shows that proposed approach is more robust and outperforms the state-of-the-art techniques.

Keywords: Glaucoma**,** Multi Color Channel, Optic Nerve Head, Feature Extraction, Image Processing, Data Mining

1. INTRODUCTION

Automated glaucoma diagnosis in a two dimensional retinal fundus image is much needed one for the early detection to stop further vision loss since glaucoma is irreversible. However this disease was identified by many features like changes in retinal stuructures, high eye pressure, retinal optic cup region size increase, thinning of blood vessels, rim thickness etc. Fig. 1 shows the anatomical changes which are used for the identification of glaucoma disease were presented. Many computer-aided approaches were presented for glaucoma retinal disease identification by Neuro retinal Rim (NRR) thickness calculation such as Cup to Disc (CDR) ratio using Optic Disc (OD) and Optic Cup (OC) segmentation, Vertical CDR (VCDR), Horizontal CDR(HCDR), OD diameter [1], Inferior Superior Nasal Temporal (ISNT) rule calculation. Mainly glaucoma occurs due to high Intra Occular Pressure (IOP) [2] leads to Optic Nerve head damage which is used to transfer the information between the retina and the brain. This causes thickening of Optic Nerve Fibre Layer (ONFL) will decrease the Neuro Retinal Rim (NRR) tissue represents the progression of glaucoma. NRR thickness for normal eye is 0.3 [3] or less and the range is greater than 0.3 considered as abnormal eye which will caused due to the increase in cupping such as OC. If the rim thickness is 0.65 [4] or greater confirms the presence of glaucoma. Segmentation of OD and OC is very time consuming [5] and risk factor task because it can mislead the automatic glaucoma diagonosis system when OD and OC region is not segmented accurately. Therefore many researches were going on for automatic detection of OD and OC and many approaches were presented by different researchers. Furthermore methods were adopted to improve the disease identification process such as VCDR, HCDR [6] and ISNT rules to increase the identification accuracy of glaucoma. By considering all the challenges stated above, we proposed an novel approach which does not need OD and OC segmentation gives 100% accuracy on RIM-ONE r1 and RIM-ONE r2 and 90.50% accuracy on Drishti-GS1 dataset proves our system efficiency. The major contribution of our work is:

1. To simplify the glaucoma identification process, we considered Optic Nerve Head (ONH) region such as around OD region for feature extraction instead of processing full fundus image.

E-mail: jeslinmalar@gmail.com, rgeetha@yahoo.com

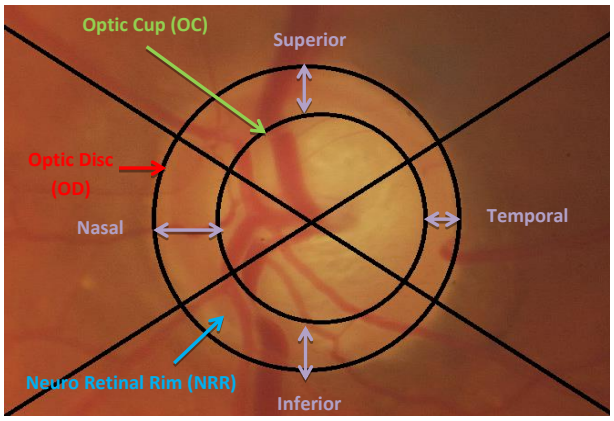


Figure 1. Retinal structural changes used for Glaucoma diagnosis

2. This process does not need accurate region segmentation represents the system will be more suitable for better disease classification.
3. A novel method of Multi color channel feature extraction is presented instead of using single color channel. This method will extract even subtle information from the image without any loss is one major advantage of our work.

This research paper is organized as follows: "Related Work" presents the overview of an approach in the field of computer-aided glaucoma disease diagnosis; "Proposed Method" depicts the overall process of our system; "Simulation Results" gives the detail description about the datasets used, performance measures used for evaluation and detailed results of glaucoma disease classification; "Conclusion and Future Works" concludes the proposed work and future works.

2. RELATED WORK

Some of the recent research works performed for glaucoma disease diagnosis throgh image processing, data mining and deep learning techniques was presented here. Arnay et al. [7] proposed an ant colony optimization-based method for OC segmentation is one of the important parameter for the identification of glaucoma disease through computerized technique. In this work was tested on RIM-ONE r1 dataset and achieved 24.3% overlapping error, 7.7% CDR error for healthy images and 7% CDR error for glaucomatous images. Their performance was compared with SiMES dataset since no CDR results for this datasets were published and this system achived 79.57% of area under the curve using CDR for glaucoma assessment. Zhou et al. [8] presented a novel approach for automatic OD and OC segmentation for glaucoma diagnosis using locally statistically active contour model with sturucture prior (LSACM-SP) in the presence of intensity inhomogeneity. This approach was tested on Drishti-GS1 dataset and RIM-ONE r2 dataset by calculating vertical CDR based on OD and OC segmentation and achieved accuracy of 89.01%, 84.69% and area under curve of 84.6%,80% for the performance of glaucoma detection. Dharmanna and Chandrappa [9] presented hausdrop fractal dimension (HFD) technique for glaucoma diagnosis by analysing Optic Nerve Head (ONH) region and reported overall fractal dimension is 0.998 for healthy OD and 1.342 for glaucomatous OD.

Haleem et al. [10] proposed a novel model to segment OD and OC for automatic glaucoma diagnosis using adaptive region-based edge smoothing model (ARESM). In this algorithm region classification model (RCM) is used to identify the boundry of OD and OC region through pixel-wise classification and the region is dynamically searched to obtain optimum contour profile. In order to avoid boundary point misclassification, adaptive edge smoothing update model (AESU) is adopted hence it doesn't need any circular or ellipse template to smoothen the selected contour points. This method tested on RIM-ONE r1 and Drishti-GS1 datasets and achieved overall vertical CDR, horizontal CDR and area CDR error of 8%, 8% and 5% for normal images and 11%, 10% and 11% for glaucomatous images. Septiarini et al. used three statistical features namely mean, smoothness and third moment features and extracted from ONH region for generating prediction model for glaucoma disease diagnosis [11]. This method presented a disease prediction model was designed by correlation feature selection method followed by K-nearest neighbour classifier. This work was tested on 84 fundus images having 43 normal images and 41 glaucomatous images with accuracy of 95.24% achieved.

Nowadays, deep learning methods are mostly used for disease diagonosis through automation system because of its increased accuracy. Shibata et al. [12] presented a deep residual learning algorithm for image recognition (ResNet) to increase the performance of glaucoma diagnosis. This work was done on 3132 color fundus images which is having 1364 glaucomatous images and 1768 normal images and tested on 110 images. In order to process the full fundus image, avoid complexity of features and misclassification, all the images were cropped in and around the OD region after that applied on ResNet deep network to extracts the detailed and complex features from the images. The performance results of this method were calculated using the area under the receiver operating characteristic curve (AROC) on the testing dataset and achieved 96.5%. Al-Bander et al. [13] proposed DenseNet with a fully convolutional network is adopted for OD and OC segmentation for glaucoma diagnosis. It contains symmetric U-shaped architecture which is used for pixel-wise classification. This approach was trained on 455 images out

of 1219 fundus images and achieved overlap of 77.08% for rim thickness calculation.

3. PROPOSED METHOD

This paper presents a novel technique for automatic diagnosis of glaucoma disease using supervised approach. The structural changes in the properties of Optic Nerve Head will help to identify many diseases like Glaucoma, Diabetic Retinopathy, and Occlusion etc. Hence, our system

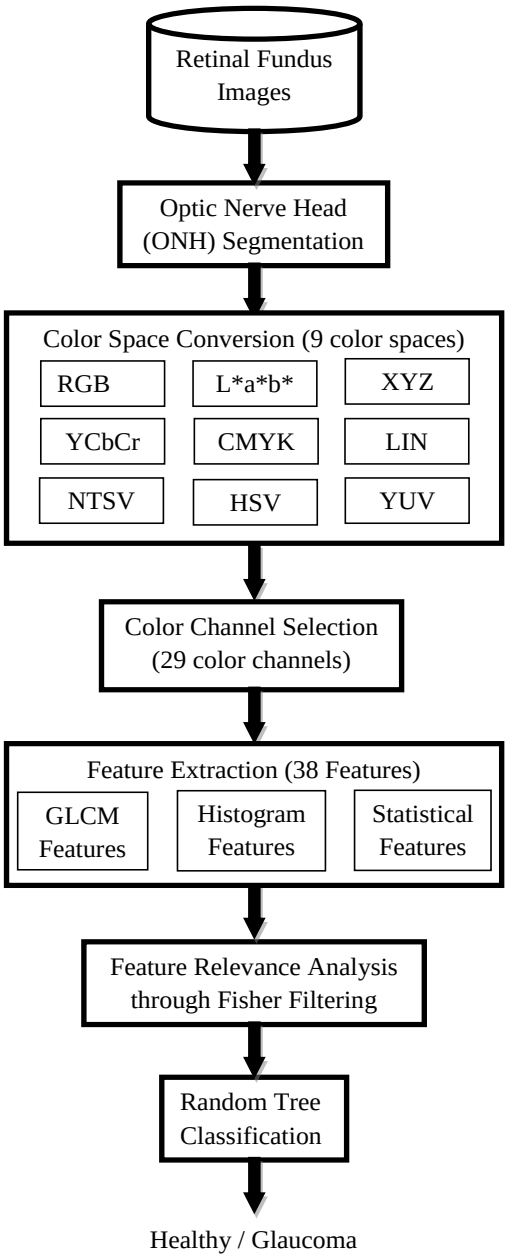


Figure 2. Overall process of proposed system

proposed set of processes as shown in Fig. 2 to extract features from ONH portion in terms of glaucoma disease classification. Proposed method is organized as seven stages namely: OD localization, ONH segmentation, color space conversion, color channel selection, feature extraction, Feature relevance analysis and Classification algorithms are detailed in the following subsections.

A. Optic Disc Localization

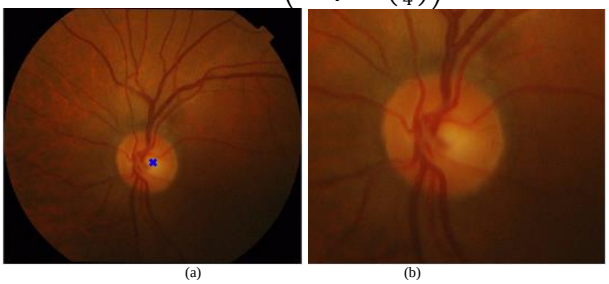
OD localization is a preliminary stage that is used to localize the OD region in order to segment the ONH portion according to the necessity of feature extraction. Hence, we employed identification of OD region through pixel density calculation [14] method and also same parameter is used such as the initial binarization threshold value and pixel density range is fixed as 0.98 and 2000. This method localizes the OD region efficiently for 101 images which is highly helpful for the automatic ONH portion segmentation processes as it does not have any negative effect on the pixel density calculation. OD localization is done on Drishti-GS1 database and achieved 100% accuracy. Remaining images of RIM-ONE r1 and RIM-ONE r2 databases are having images of ONH portion only therefore directly used for color space conversion instead of OD localization process.

B. Optic Nerve Head Segmentation

After OD localization, ONH is cropped by using coordinates of OD localization point which is calculated from previous step. For this cropping, row and column size of an image is calculated and rectangle window template [14] is created with the help of coordinate points of OD localization point. Since we are using Drishti-GS1 database and it contains different resolution size images i.e. one of the image resolution size is 2045 x 1751. Hence, the proposed algorithm used original image size for creating rectangle window template to crop ONH portion. The equation used for rectangle template is explained in (1-3).

$$X_{start} = \text{round}\left(Loc_x - \left(\frac{I_C}{4}\right)\right) \quad (1)$$

$$Y_{start} = \text{round}\left(Loc_y - \left(\frac{I_R}{4}\right)\right) \quad (2)$$



(a) (b)

Figure 3. Optic nerve head segmentation. (a) Localized optic disc with coordinate points x=1032 and y=1062 (b) Segmented optic nerve head region

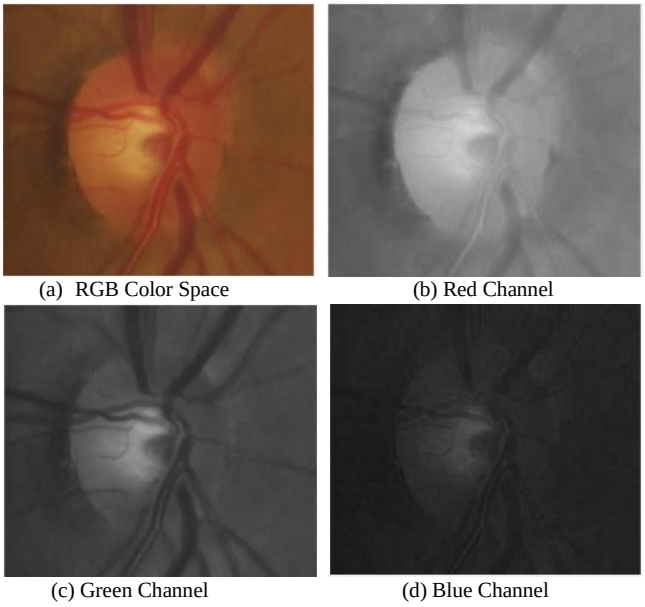
$$RWT = \left[X_{start}, Y_{start}, \frac{I_C}{2}, \frac{I_R}{2}\right] \quad (3)$$

Where X_{start} & Y_{start} represents the starting position of an image, I_C & I_R represents the row and column size of an image, RWT is a rectangle window template and Loc_x & Loc_y represents the coordinate points of a localized OD. In order to reduce the cropping size of ONH region i.e. below 500 x 500 resolutions, the algorithm divided the row and column size of an image by 4 for calculating starting cropping position of an image and also height and width of an image size is reduced to half size for all the images of Drishti-GS1database, because small size of ONH region is enough for feature extraction. Fig. 3 show the template creation process followed for ONH segmentation.

C. Color Space Conversion and Color Channel Selection

Proposed approach novelty is based on multiple Color channel used for ONH feature extraction which is unique comparing to other existing approaches [6, 15–17] . Color space is mostly composed of three color channels and is a good way to visualize the color range within an image and also each and every color channel holds different variety of color ranges which can clearly represents the changes between pixel to pixel more clearly. Retinal diseases were analyzed on retinal fundus images mostly through intensity based approaches [18, 19]. However, existing approaches used different color channels [20, 21] for preprocessing stage before feature extraction as well as segmenting OD and OC region in terms of Glaucoma disease identification. In our proposed system, we used nine color spaces and selected 28 color channels out of 9 color spaces and gray channel for ONH feature extraction without image processing as well as OD and OC region segmentation. This technique is more robust and very much unique unlike other approaches was one of the best outcomes of our system. Proposed system was mainly focused on identification of retinal diseases through feature extraction in order to avoid pathological region segmentation problem which is very complex due to disease distractions in the retinal fundus images. Hence, our approach analyzed the proposed method with RGB, XYZ, LIN, La*b*, NTSC, HSV, CMYK, YUV, YC_bC_r color spaces and gray color channel in order to extract the subtle features which is very much useful during disease classification. Color channel conversion is obtained using Matlab inbuilt functions and detailed below.

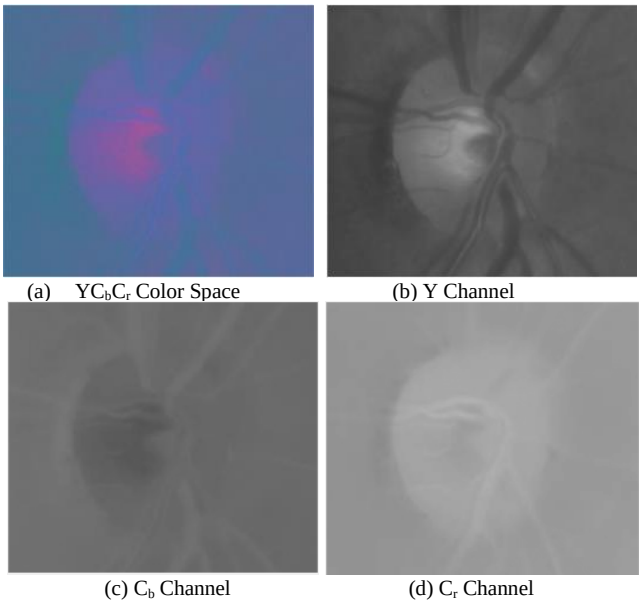
1) *RGB Color Space:* Retinal color fundus images used for this approach were in the form of RGB color space. RGB color space is a color model with three dimensions – Red, Green and Blue. So from RGB images we mined three channels Red Channel (R), Green Channel (G) and Blue Channel (B) for feature extraction. Fig. 4 shows that original color space and its corresponding color channels.



(a) RGB Color Space (b) Red Channel

(c) Green Channel (d) Blue Channel

Figure 4.RGB Color Space and its corresponding Color Channels



(a) YC_bC_r Color Space (b) Y Channel

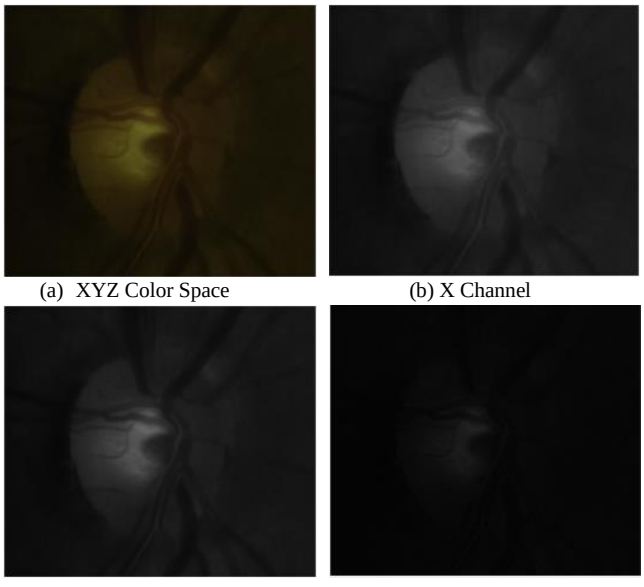
(c) C_b Channel (d) C_r Channel

Figure. 5. YCbCr Color Space and its corresponding Color Channels

2) *YC_bC_r Color Space:* YC_bC_r color space is one of the primary color spaces like RGB which is used to represent digital component video. In order to compute more color intensities, retinal fundus images are converted from RGB color space into YC_bC_r color space in associations with better feature extraction. Y contains luminance information which represents the brightness of R, G, B colors and is stored as a single component and C_b & C_r contains blue difference, red difference chrominance information and stored as two color difference component. Fig. 5 shows YC_bC_r Color space and its corresponding color channels.

3) *XYZ Color Space:* CIE 1931 XYZ is a device-invariant color space because this color space encompasses all color sensations that are visible to a person with average sight and it is developed by the international commission on illumination (CIE). In XYZ color space: Y represents luminance, Z represents the amount of blue in an image but not equal as blue channel from RGB color space, X represents orthogonal to the Y channel and positive value and it also stated as tristimulus values. This color space represents the extrapolations of RGB color space which is created mathematically by including only positive numbers. Fig. 6 shows the conversion from RGB color space to XYZ color space and its corresponding color channels.

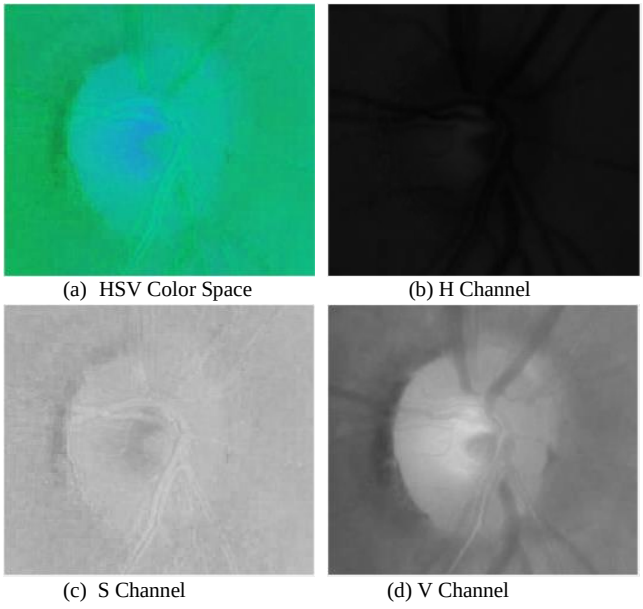
4) HSV Color Space: HSV (Hue, Saturation, Value) color model is designed based on human observation and understanding of color such as using color palette or color wheel for color selection. This color space contains intensity component decoupled from the color information and also contains high saturation range. Here, H defines the color position, S represents the degree of hue difference and V represents maximum intensity component value i.e. high value among red, green and blue color components. Fig. 7 shows HSV color space from RGB color space and its three channels.



(a) XYZ Color Space (b) X Channel

(c) Y Channel (d) Z Channel

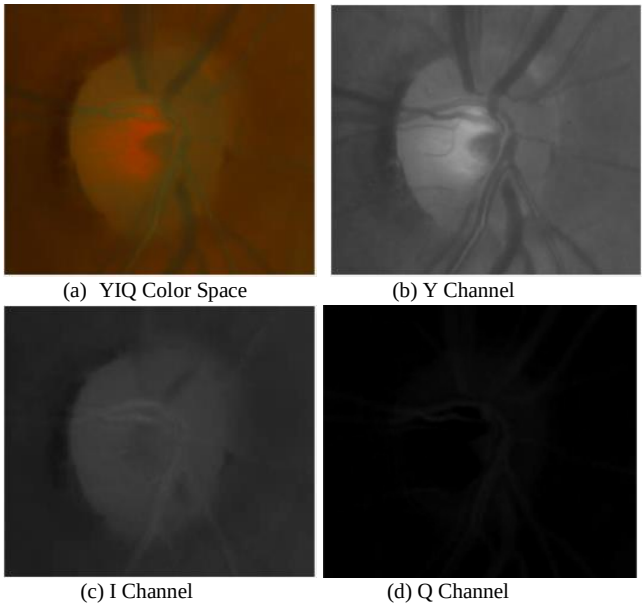
Figure 6 ..YZ Color Space and its corresponding Color Channels



(a) HSV Color Space (b) H Channel

(c) S Channel (d) V Channel

Figure 7. HSV Color Space and its corresponding Color Channels

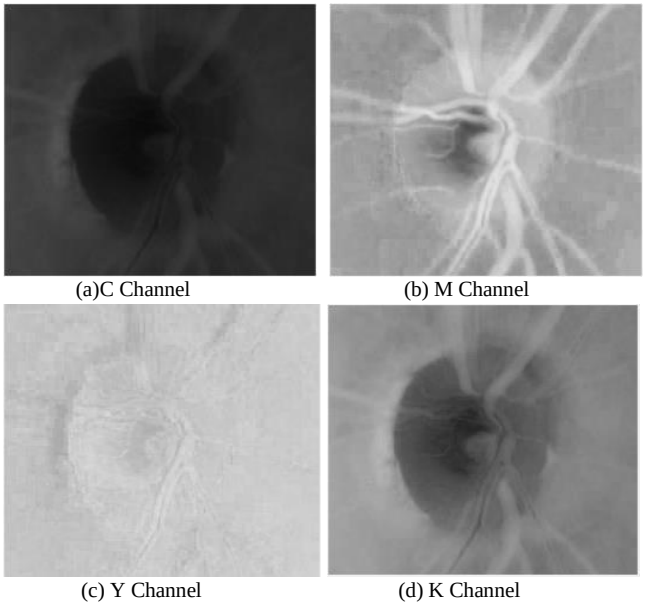


(a) YIQ Color Space (b) Y Channel

(c) I Channel (d) Q Channel

Figure 8. YIQ Color Space and its corresponding Color Channels

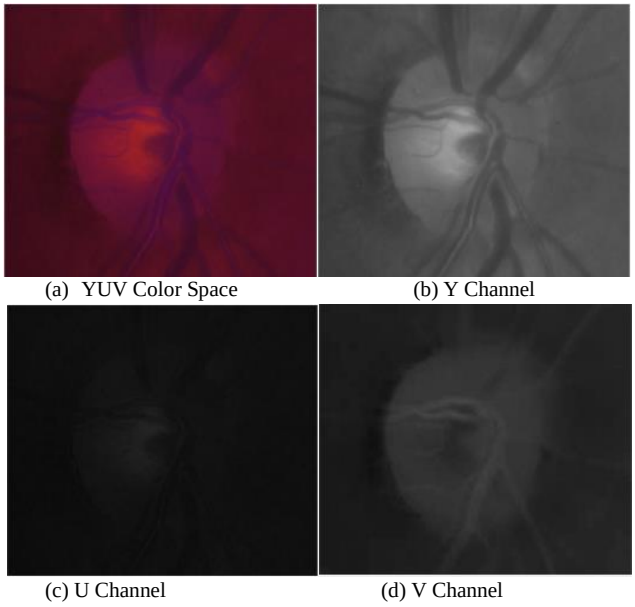
5) *YIQ Color Space:* YIQ (Luma, In-phase, Quadrature) color space model is defined by NTSC (National Television Systems Committee) which can be useful for segregating grayscale information from an image. It comprises of luminance/brightness of an image (Y), blue/orange chrominance of an image (I) and green/purple chrominance of an image (Q). Fig. 8 shows YIQ color space converted from RGB color space and its corresponding color channels.



(a)C Channel (b) M Channel

(c) Y Channel (d) K Channel

Figure 9. Four Color channels from CMYK Color Space



(a) YUV Color Space (b) Y Channel

(c) U Channel (d) V Channel

Figure. 10. YUV Color Space and its corresponding Color Channels

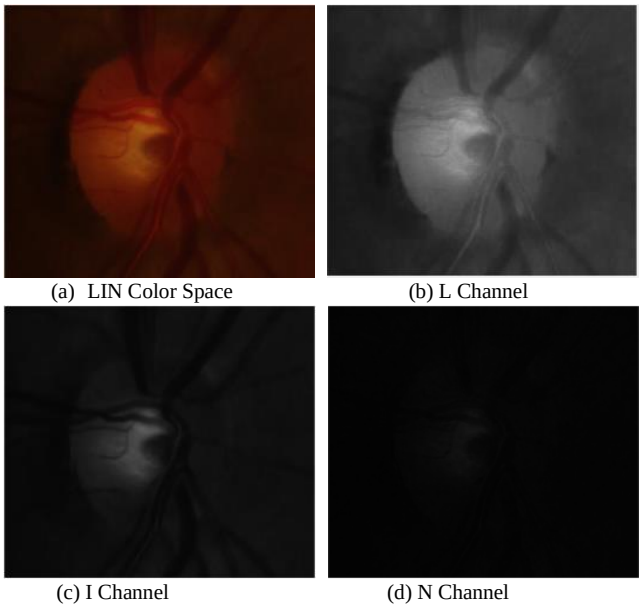
6) *CMYK Color Space:* CMYK (Cyan, Magenta, Yellow, Key) color space is the subset of RGB color space and used for color print production. This color space is stated as subtractive color model because it creates final color by subtracting CMY colors from the white surface. CMYK referred as primary colors of pigment such as cyan, magenta, yellow and black. Fig. 9 shows four color channel of CMYK color space.

7) *YUV Color Space:* YUV color space is a basic color model derived from RGB color space and it comprises of luminance (Y) component computed by weighted sum of red, green, and blue color channels, and chrominance components (U & Y) computed by subtracting the color difference blue and red color component. Fig. 10 shows the results of YUV color space conversion along with three color channels. Conversion from RGB color space to YUV color space is calculated by using the below equation as in (4-6).

$$Y = red * (0.299000) + green * (0.587000) + blue * (0.114000) \quad (4)$$

$$U = red * (-0.168736) + green * (-0.331264) + blue * (0.500000) + 128 \quad (5)$$

$$V = red * (0.500000) + green * (-0.418688) + blue * (-0.081312) + 128 \quad (6)$$



(a) LIN Color Space (b) L Channel

(c) I Channel (d) N Channel

Figure. 11. LIN Color Space and its corresponding Color Channels

8) *Linearized Gamma-corrected RGB Color Space (LIN):* Linearized gamma-corrected color space presents brighter image than linear RGB color space. Doubling the value of a color space is a linear color space used to increase the brightness and contrast of an image twice. Here, RGB color space is converted to linearized gamma-corrected color space by using Matlab inbuilt function with default parameter. Fig. 11 shows the linearized gamma-corrected RGB color space and its corresponding color channels.

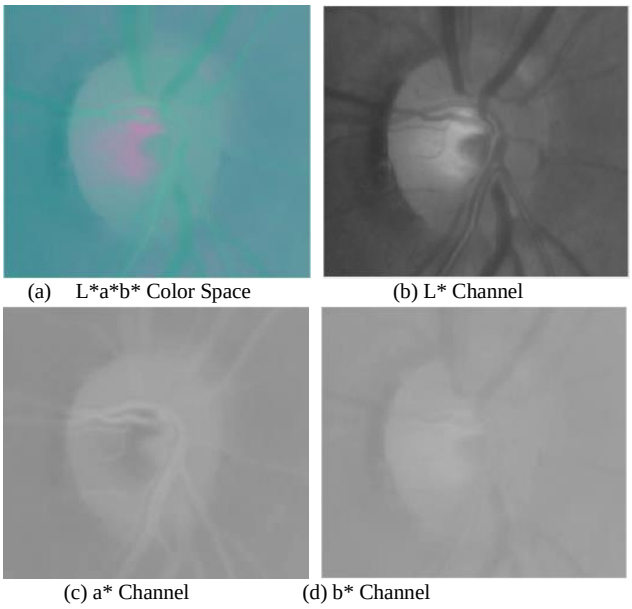


Figure. 12. La*b* Color Space and its corresponding Color Channels

9) *L*a*b* Color Space:* CIE 1976 L*a*b* color model [22] is a device-independent color space developed by CIE which provides perceptual uniform color space derived from standard CIE XYZ color space and designed based on sensitivity of cone cells in the human eye. It comprises Luminance (L*) of an image, red/green chrominance (a*) of an image and also yellow/blue chrominance (b*) of an image. Fig. 12 shows the color conversion from RGB color space to L*a*b* color space along with three color channels.

D. Feature Extraction

Feature extraction (FE) and normalization stages are very important to diagnose the retinal diseases through classification algorithms. To make an automatic classification approach, our proposed system extracted features using image processing techniques using Matlab software. Automatic classification approach for glaucoma disease identifications are detailed below. Most important stage of our proposed approach is Feature extraction which is used to quantify the ONH surface through different texture parameters. Because glaucoma identification through OD & OC segmentation and ISNT rule computation is very much difficult while processing heterogeneous images such as intensity, resolution and pathological images. However, extractions of image features were much efficient to identify Glaucoma retinal disease rather than segmenting the pathological regions. In order to improve the performance accuracy of glaucoma disease classification process, our proposed system extracted Gray Level Concurrence Matrix (GLCM), Statistical and Histogram features from 29 color channels though image processing. In our approach, 38 features were extracted from each color channel and totally considered as 1102 features for each ONH region. Features extracted from each color channel are presented in sub sections.

E. Statistical Features

Statistical features[23–25] are extracted from all the converted color channels of an ONH portion. Proposed system extracted eleven statistical features: mean, median, mode, root mean square (RMS), minimum intensity, maximum intensity, standard deviation, covariance, variance, correlation coefficient (CC) and entropy from ONH region. Texture of an image surface can be defined using Statistical feature extraction methods and it extracts the information based on neighborhood pixels and gray level intensity pixels. Eleven common statistical features are extracted from ONH region for all the selected color channels and used for glaucoma identification.

F. Gray Level Co-occurrence Matrix Features

Proposed approach, Gray Level Co-occurrence Matrix (GLCM) method is used to extract twenty two textural features which were used for glaucoma disease diagnosis. Features extracted for GLCM [24, 26, 27] method: energy, entropy, dissimilarity, contrast, inverse difference (ID), correlation, homogeneity, auto correlation, cluster shade, cluster prominence, maximum probability, sum of squares (SOS), sum of average (SOA), sum of variance (SOV), sum of entropy (SOE), difference variance, difference entropy, information measure of correlation1 (IMC1), IMC2, maximal CC, ID normalized, and ID moment normalized. This function characterizes the texture of a surface specifically through intensities, relationship and closeness such as calculating the intensities of a pair of pixel, spatial relationship and distribution of elements from nerve head region. GLCM method extracts second order statistical texture features by using gray-level spatial dependence matrix and 22 textural features were extracted.

G. Histogram Features

Histogram based features [24] are represented as first order statistical texture features extracts the information from each pixel instead of considering the relationship among each pixels. Histogram based features concentrates on image intensities of overall image or some portion of an image is used for glaucoma identification. For this work we used ONH region and features extracted are: skewness, kurtosis, mean, variance and energy.

H. Feature Relevance Analysis

In supervised approach, feature relevance analysis plays a major role to improve the performance of the system through selecting relevant features from the extracted features. This normalization is much needed one while using large number of features and also it will not consider redundant feature is added advantage during learning. Proposed system adopted three feature selection algorithms

namely fisher filtering, relief filtering and runs filtering to generate better prediction model for glaucoma diagnosis. Relevant features are analyzed individually through learning algorithm and it ranks the features based on its relevance. The evaluation and results of feature selection methods are detailed in results and discussion section.

I. Classification Algorithm

For glaucoma disease classification, initially we adopted 15 classifiers namely BVM (Ball Vector Machine), C4.5 (Decision Tree), C-RT (Classification Tree), CS-CRT (Cost Sensitive Classification), CS-MC4 (Cost Sensitive Decision Tree), C-SVC (SVM for classification), CVM (Core Vector Machine), ID3 (Iterative Dichomotiser), K-NN (K-nearest Neighbor), Multilayer Perceptron, Multinomial Logistic Regression, Naïve Bayes Continuous, PLS-DA (PLS for Discrimination), PLS-LDA (Combination of PLS and Linear Discriminant Analysis), Random Tree and its error rates were measured in order to identify the classifier which supports glaucoma diagnosis more. From that analysis, our approach selected seven classifiers for further process and results were presented in results and discussion section.

4. RESULTS AND DISCUSSION

In this section presents the datasets used for this approach, performance results of our proposed system and the results of all the datasets used for glaucoma disease classification. Fisher filtering feature selection algorithm was applied on overall extracted features to select suitable features for disease identification followed by random tree algorithm to identify the presence of glaucoma disease on three publically available datasets with two cross validation. Most of the existing techniques used different color channel for glaucoma disease identification. In our approach, 29 color channels were used is novel approach and so far researchers have not implemented on retinal fundus images. Henceforth a novel multi color channel feature extraction technique was applied on retinal fundus images and classified using random tree algorithm achieved positive predictive value of 100% on RIM-ONE r1 and RIM-ONE r2 dataset and 93.89% on Drishti-GS1 dataset in terms of glaucoma disease classification.

A. Dataset Description

Drishti-GS1dataset [28] consists of 101 color fundus images with different resolution of sizes i.e. from 2045 x 1752 to 2466 x 1763 resolution size. All images of Drishti-GS1 dataset were taken with a Field-of-View (FOV) of 30° and positioned on OD region. This dataset is used for validating OD region, OC region and detection notching. Images in this dataset is divided into two parts contain 50 training images and 51 testing images and also contains ground truths for segmentation soft map, average OD and cup boundaries, CDR values, image level decisions and notching. RIM-ONE r1 (An Open Retinal Image Database for Optic Nerve Evaluation release1) database [29] contains 169 retinal fundus images with high-resolution and five soft map of OD segmentation for each images were presented. This dataset mainly used for glaucoma disease diagnosis and it also contains images from healthy eyes as well as eyes with different stages of glaucoma. Ground truth of glaucoma disease images with different stages which is represented as early, moderate, deep and Ocular Hypertension (OHT) image ground truth were provided by experts. RIM-ONE r2 (An Open Retinal Image Database for Optic Nerve Evaluation release2) database [29] contains 455 high-resolution fundus images with ground truth of image level glaucoma diagnosis. This dataset contains image level diagnosis of images from healthy eyes, glaucoma eyes and glaucoma suspicious eyes.

B. Implementation Environment

The proposed glaucoma classification system was implemented using Matlab 2017b and its inbuilt functions are used for image processing techniques and Tanagra data mining tool used for disease classification. For this work, totally 725 images from three publically available datasets were analyzed, features extracted and evaluated with the ground truth given by the experts through cross validation.

C. Simulation Results

This section presents the sample results of each steps were processed for glaucoma classification. In first step, fundus images from Drishti-GS1 dataset were applied on OD localization in order to segment the ONH portion from the overall image. Remaining datasets such as RIM-ONE r1and RIM-ONE r2 having the images of optic nerve head segmented region unlike full fundus images. Second step: ONH segmented images from three datasets were converted to different color spaces from RGB color space using Matlab built-in functions. Hence 28 color channels are selected from 9 color spaces for each image and also RGB color space is further converted to gray color channel was too added. So, totally 29 color channels were selected for feature extraction process for an image. Third step: GLCM, statistical and histogram features i.e. 38 features were extracted for each color channel from each images for disease classification. For this work our approach used 725 ONH segmented images and extracted 1102 features for an image. Hence totally 798950 features were extracted for all the images from three publically available dataset that was too huge when compared with previous approaches.

Fourth step, in order to reduce the complexity and error rate of disease classification our approach adopted feature relevance analysis such as Fisher filtering, Relief filtering and Runs Filtering algorithm. Before feature selection, our approach analyzed the extracted features with fifteen classification algorithms and its error rates were noted for further process.

Table 1 shows the error rate measures before applying feature selection on different classifiers in the process of glaucoma disease classification for Drishti-GS1, RIM-ONE r1 and RIM-ONE r2 datasets. Based on observation, classifiers having greater than 20% error rate were eliminated from further process to reduce the computation process complexity.

Hence, seven classifiers namely Ball Vector Machine, C4.5 Decision Tree, Cost Sensitive Decision Tree, SVM for Classification, Core Vector Machine, Multilayer Perceptron and Random Tree were selected for feature relevance analysis.

Table 2-4 shows the features selected from overall features through feature relevance analysis of three datasets were presented individually. From the evaluation results we observed out of three feature selection algorithm fisher filtering algorithm chosen minimal features compared with other two algorithms for three datasets. Final step was random tree classification classifies glaucoma disease and achieves better sensitivity of 100%, 100% and 91.79% on RIM-ONE r1, RIM-ONE r2 and Drishti-GS1 dataset.

TABLE I. ERROR RATE MEASURES OF DIFFERENT CLASSIFIERS IN THE DETECTION OF GLAUCOMA DISEASE

S. No.	Classifier Name	Error Rate Performances (%)		
		DRISHTI	RIM-ONE r1	RIM-ONE r2
1	Ball Vector Machine	13%	0	3.74%
2	C4.5 - Decision Tree	5%	7.14%	7.49%
3	C-RT Classification Tree	33%	23.81%	25.11%
4	CS-CRT Cost Sensitive Classification	33%	23.81%	25.11%
5	CS-MC4 Cost Sensitive Decision Tree	6%	7.74%	4.19%
6	C-SVC	0	0	2.86%
7	CVM - Core Vector Machine	0	0	0
8	ID3 - Iterative Dichomotiser	33%	23.81%	24.89%
9	K-NN - K-nearest Neighbor	33%	76.19%	44.05%
10	Multilayer Perceptron	10%	5.36%	3.52%
11	Multinomial Logistic Regression	54%	56.55%	39.87%
12	Naïve Bayes Continuous	39%	30.36%	25.11%
13	PLS-DA	0	76.19%	44.05%
14	PLS-LDA	0	76.19%	44.05%
15	Random Tree	0	0	0

TABLE II. FEATURES SELECTED FOR RIM-ONE R1 DATASET FROM DIFFERENT CHANNELS

S. No.	Feature Selection Algorithm	Total No. of Features	Features Selected for RIM-ONE r1 Dataset
1	Fisher Filtering	5	**Maximum intensity:** A* from L*A*B* color space Q from YIQ color space Cr from YC_bC_r color space M from CMYK color space V from YUV color space
2	Relief Filtering	5	**Maximum Intensity & Minimum Intensity:** H from HSV color space **Correlation, Histogram Variance & Histogram Energy**: Q from YIQ color space
3	Runs Filtering	15	**Maximum Intensity, Histogram Variance, Histogram Energy, & Histogram Mean:** Q from YIQ color space **Entropy:** I from YIQ color space K from CMYK color space **Mode:** C from CMYK color space **Energy:** L from LIN color space **H from HSV color space** Green from RGB color space **Histogram Skewness:** H from HSV color space **GLCM Cluster Prominence:** Red from RGB color space Cr from YC_bC_r color space V from HSV color space **GLCM Information Measure of Correlation2:** I from YIQ color space

D. Performance Evaluation

The performance measures such as [14] sensitivity, accuracy and positive predictive value were calculated for all the fundus images and results were noted. The sensitivity (SE) also called as true positive rate which measures the percentage of correctly predicted glaucoma presence from total number of glaucoma presence and is defined as follows

$$\text{Sensitivity (SN)} = \frac{\text{TP}}{\text{TP+FN}} \times 100\% \qquad (7)$$

Accuracy (AC) is a measure require high precision and high trueness which measures the percentage of correctly classified observations of glaucoma presence as well as absence and is defined as follows

$$\text{Accuracy (AC)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100\% \qquad (8)$$

The positive predictive value (PPV) also called as precision which measures the percentage of correctly predicted glaucoma presence from total number of predicted glaucoma presence and is defined as follows

$$PPV = \frac{TP}{TP+FP} \times 100\% \quad (9)$$

TABLE III. FEATURES SELECTED FOR RIM-ONE R2 DATASET FROM DIFFERENT CHANNELS

S. No.	Feature Selection Algorithm	Total No. of Features	Features Selected for RIM-ONE r2 Dataset
1	Fisher Filtering	6	**Maximum intensity:** B* from L*A*B* color space, Q from YIQ color space, Cr from YC_bC_r color space, V from YUV color space **GLCM Entropy:** L from LIN color space **GLCM Information Measure of Correlation1:** Q from YIQ color space
2	Relief Filtering	10	**Maximum Intensity:** H from HSV color space, Q from YIQ color space **Covariance, GLCM Information Measure of Correlation2, GLCM Sum of Variance, Histogram Variance & Histogram Energy:** Q from YIQ color space **GLCM Information Measure of Correlation1:** Q from YIQ color space, H from HSV color space **GLCM Maximum Probability:** Blue from RGB color space
3	Runs Filtering	5	**Maximum Intensity, GLCM Dissimilarity, GLGM Contrast, GLCM Difference Variance and GLCM Difference Entropy:** Q from YIQ color space

Table 5-7 shows the performance results of different classification algorithm with three feature selection algorithms were analyzed and listed. Our experiment result shows that Random tree with fisher filtering as well as Random tree with Relief Filtering gives 100% accuracy in glaucoma disease classification compared with other classifiers and feature selection algorithms. Again proposed approach cross validated three feature selection algorithms with seven classifiers and its results were noted.

TABLE IV. FEATURES SELECTED FOR DRISHTI-GS1 DATASET FROM DIFFERENT CHANNELS

S. No.	Features Selection Algorithm	Total No. of Features	Features Selected for Drishti-GS1 Dataset
1	Fisher Filtering	4	**Mode:** L* from L*A*B* color space **Histogram Variance, Histogram Energy & Histogram Mean:** Q from YIQ color space
2	Relief Filtering	10	**Maximum Intensity:** S from HSV color space, Q from YIQ color space **Minimum Intensity:** N from LIN color space **Energy:** X from XYZ color space **Histogram Mean & Histogram Variance:** Blue from RGB color space **Histogram Energy:** Blue from RGB color space, I from YIQ color space **GLCM Information Measure of Correlation1:** U from YUV color space, H from HSV color space
3	Runs Filtering	12	**Mode:** Red from RGB color space, V from HSV color space, K from CMYK color space **Histogram Variance:** Q from YIQ color space **Histogram Mean:** Green from RGB color space **Histogram Skewness:** C from CMYK color space **GLCM Inverse Difference Moment Normalized:** X from XYZ color space, L from LIN color space **GLCM Cluster Prominence:** Y from YC_bC_r color space **GLCM Correlation:** X from XYZ color space **GLCM Auto Correlation & GLCM Sum of Squares:** I from LIN color space

TABLE V. GLAUCOMA DISEASE CLASSIFICATION AFTER FEATURE SELECTION IN RIM-ONE R1 DATASET

S. No.	Classifier Name	Accuracy (%)		
		Fisher Filtering	Relief Filtering	Runs Filtering
1	Ball Vector Machine	77.98%	81.55%	92.86%
2	C4.5 - Decision Tree	85.71%	81.55%	91.67%
3	CS-MC4	76.19%	81.55%	88.10%
4	C-SVC - SVM for classification	77.98%	78.57%	80.95%
5	CVM - Core Vector Machine	78.57%	81.55%	95.24%
6	Multilayer Perceptron	79.17%	77.38%	84.52%
7	Random Tree	100%	100%	100%

TABLE VI. GLAUCOMA DISEASE CLASSIFICATION AFTER FEATURE SELECTION IN RIM-ONE R2 DATASET

S. No.	Classifier Name	Accuracy (%)		
		Fisher Filtering	Relief Filtering	Runs Filtering
1	Ball Vector Machine	75.55%	85.24%	74.67%
2	C4.5 - Decision Tree	83.70%	90.31%	76.43%
3	CS-MC4 Cost Sensitive Decision Tree	75.11%	82.60%	74.89%
4	C-SVC - SVM for classification	73.57%	77.09%	72.69%
5	CVM - Core Vector Machine	76.21%	86.12%	74.67%
6	Multilayer Perceptron	70.70%	75.11%	71.15%
7	Random Tree	100%	100%	85.46%

TABLE VII. GLAUCOMA DISEASE CLASSIFICATION AFTER FEATURE SELECTION IN DRISHTI-GS1 DATASET

S. No.	Classifier Name	Accuracy (%)		
		Fisher Filtering	Relief Filtering	Runs Filtering
1	Ball Vector Machine	73%	85%	80%
2	C4.5 - Decision Tree	67%	79%	89%
3	CS-MC4 Cost Sensitive Decision Tree	67%	67%	74%
4	C-SVC - SVM for classification	69%	72%	67%
5	CVM - Core Vector Machine	72%	87%	83%
6	Multilayer Perceptron	69%	73%	71%
7	Random Tree	100%	100%	100%

TABLE VIII. VALIDATAION RESULTS OF GLAUCOMA DISEASE CLASSIFICATION IN RIM-ONE R1 DATASET

S. No.	Classifier Name	Accuracy (%)		
		Fisher Filtering	Relief Filtering	Runs Filtering
1	Ball Vector Machine	77.98%	76.79%	75.30%
2	C4.5 - Decision Tree	85.71%	74.11%	73.81%
3	CS-MC4 Cost Sensitive Decision Tree	76.19%	74.70%	75.89%
4	C-SVC - SVM for classification	77.98%	77.38%	75.30%
5	CVM - Core Vector Machine	78.57%	76.19%	76.79%
6	Multilayer Perceptron	79.17%	75.60%	75.00%
7	Random Tree	100%	71.13%	66.37%

Table 8-10 shows the performance results of feature selection algorithm of all the three datasets with two cross validation were presented individually. Table 11 presents the overall performance results of three datasets in terms of Accuracy, Sensitivity and PPV. Random tree classification through fisher filtering algorithm with two cross validation achieved overall accuracy, sensitivity, PPV of 96.83%, 97.26%, 97.96% represents the proposed system efficiency and very much competitive with other existing approaches.

TABLE IX. VALIDATAION RESULTS OF GLAUCOMA DISEASE CLASSIFICATION IN RIM-ONE R2 DATASET

S. No.	Classifier Name	Accuracy (%)		
		Fisher Filtering	Relief Filtering	Runs Filtering
1	Ball Vector Machine	75.55%	69.93%	74.67%
2	C4.5 - Decision Tree	83.70%	68.17%	76.43%
3	CS-MC4 Cost Sensitive Decision Tree	75.11%	66.08%	74.89%
4	C-SVC - SVM for classification	73.57%	70.26%	72.69%
5	CVM - Core Vector Machine	76.21%	70.37%	74.67%
6	Multilayer Perceptron	70.70%	72.58%	71.15%
7	Random Tree	100%	68.83%	85.46%

TABLE X. VALIDATAION RESULTS OF GLAUCOMA DISEASE CLASSIFICATION IN DRISHTI-GS1DATASET

S. No.	Classifier Name	Accuracy (%)		
		Fisher Filtering	Relief Filtering	Runs Filtering
1	Ball Vector Machine	71.50%	52.00%	59.00%
2	C4.5 - Decision Tree	65.00%	49.50%	49.50%
3	CS-MC4 Cost Sensitive Decision Tree	65.00%	52.50%	56.00%
4	C-SVC - SVM for classification	69.00%	57.50%	59.00%
5	CVM - Core Vector Machine	68.50%	51.50%	59.50%
6	Multilayer Perceptron	67.00%	49.50%	51.50%
7	Random Tree	90.50%	53.00%	45.00%

TABLE XI. OVERALL PERFORMANCE RESULTS OF GLAUCOMA DISEASE CLASSIFICATION

S. No.	Dataset	Accuracy (%)	Sensitivity (%)	PPV (%)
1	RIM-ONE r1	100%	100%	100%
2	RIM-ONE r2	100%	100%	100%
3	Drishti-GS1	90.50%	91.79%	93.89%

Table 12 presents the comparative analysis of proposed system with recent approaches. However, it is difficult to compare exact dataset with existing techniques so our system compared the overall performance with existing techniques. For this performance analysis, we compared existing techniques of rim-to-disc ratio(RDR) and disc-damage-likelihood scale (DDLS) [30], multi-task convolutional neural network [31], intensity based approach using image processing techniques (IBA) [32], Watershed Transformation (WT) [33] , Region growing (RG) and WT [34] and Multivariate mediod (MM) based classifier [4]. Fig. 13 presents the graphical representation of proposed approach performance results were compared with the existing techniques in terms of accuracy and sensitivity.

TABLE XII. COMPARISON OF PROPOSED APPROACH WITH THE STATE-OF-THE-ART METHOD IN TERMS OF ACCURACY AND SENSITIVITY

No.	Author	Method	Accuracy	Sensitivity
1.	Kumar et al. 2018 [30]	RDR+DDLS	89.91%	85.38%
2.	Chakravarthy et. al. 2018 [31]	CNN	89.50%	88.00%
3.	Manju et al. 2018 [32]	IBA	75.00%	71.40%
4.	Das et al. 2016 [33]	WT	94.14%	91.82%
5.	Nirmala et al. 2016 [34]	RG+WT	93.85%	92.59%
6.	Akram et al. 2015 [4]	MM	90.84%	85.72%
7.	**Proposed Method**	ONH + Multi Color channel FE	**96.83%**	**97.26%**

TABLE XIII. DISEASE CLASSIFICATION USING DEEP LEARNING NETWORK

No.	Deep Learning Network	Train:Test	Accuracy
1	Feature Input Layer	80:20	88.89%
2	Feature Input Layer + LSTM Layer	80:20	79.41%
3	Feature Input Layer + BiLSTM Layer	80:20	82.35%

Simple deep learning network with seven network layers such as feature input layer, two fully connected layer, batch normalization layer, relu layer, softmax layer & classification layer is designed to analyze extracted features. For this work, Z score normalization is adopted to normalize the features before classification and total instances are divided into 80:20 for training and testing with 0.01 and 15 of learning rate and mini batch size. Table 13 presents the validation results of simple deep learning network evaluated using features obtained from proposed approach and the results shows that our system gives better disease prediction accuracy comparing to deep learning network classification.

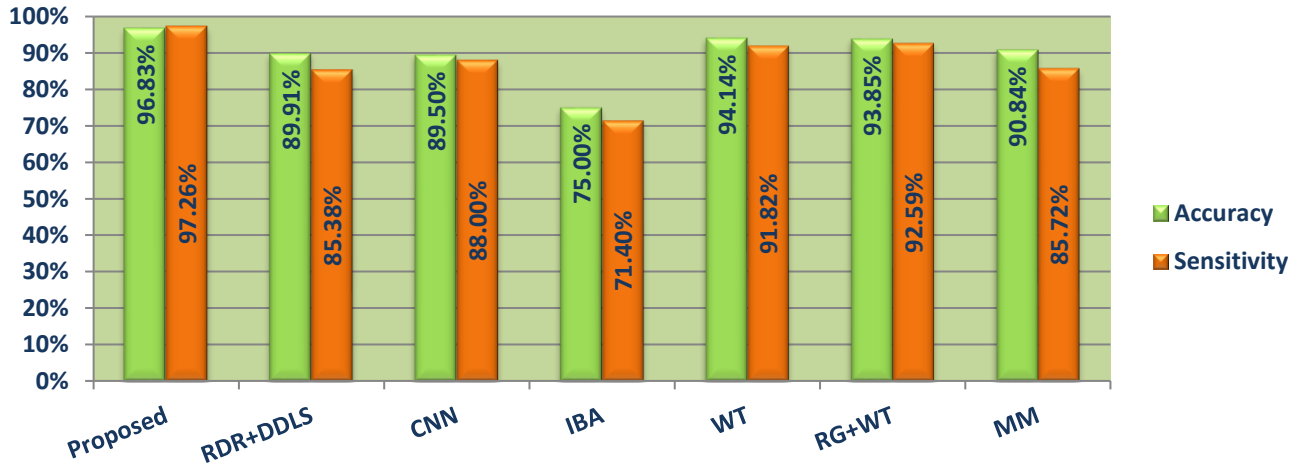


Figure 13. Performance analyses of overall images with existing techniques in terms of sensitivity and accuracy

Here, X axis represents different glaucoma disease identification approaches along with proposed approach and Y axis shows the accuracy of different approaches along with proposed system accuracy was presented. However, existing glaucoma disease identification technique was failed mainly because of low level OD region segmentation accuracy either poor quality of images nor pathological distractions even though well performed algorithm is used. In order to avoid that misclassification process, novel method using multi color channel feature extraction from ONH region has been chosen to overcome the complication of OD region segmentation process while identifying glaucoma retinal disease using random tree classification.

5. CONCLUSION AND FUTURE WORK

Our proposed system contribution is considered as very important in glaucoma disease classification process. Proposed algorithm presented a novel technique to classify glaucoma disease through image processing and data mining techniques. Advantage of this algorithm is the ability to classify the disease automatically without any manual effort represents the system robustness. Our approach has the capability to identify the disease with very few features as well as very minimal image processing techniques represents the system efficiency. In general, glaucoma disease is identified mainly through OD region of retina such as OD localization, OD segmentation, OC segmentation, as well as the value such as Cup to Disc Ratio, ISNT rule etc. calculated through these regions are considered for glaucoma disease identification parameters which is very much difficult due to other pathological distractions such as fundus image quality, blood vessel distraction, exudates presence, peripapillary distraction etc. During this process segmentation accuracy is much important while identifying glaucoma disease. Due to pathological distractions segmentation of OD and OC region is much complex as stated in existing techniques. Instead of using those measurements we presented a novel and simple

approach with good performance results states the proposed approach competency and impeccability. In order to avoid those complications and to improve the segmentation accuracy we adopted novel technique which extracts features from Optic Nerve Head (ONH) region for glaucoma disease identification. This method is considered as unique and efficient because instead of processing whole fundus image our approach selected ONH region through OD localization is much efficient and other distractions like bright cotton wool spots, hemorrhages, exudates etc. will be avoided. Proposed system doesn't need any technique for region segmentation, improvisation in region segmentation accuracy and no need to process full retinal fundus image which is proven as very efficient based on our disease identification results. Many existing techniques adopted different color channel for region segmentation and feature extraction process to extract useful information which gives better disease identification but our approach chosen multi color channels for feature extraction process to identify the disease. Proposed system selected 29 color channels for feature extraction process which will extracts useful and different intense features are more suitable for glaucoma disease classification process. Proposed system achieved overall PPV of 97.96% which is higher than other existing techniques represents the proposed system competency. The performance of the proposed approach was compared with existing approaches depicts the proposed algorithm adeptness. In feature work, the feature extraction will be improved with segmentation of OD and OC region, CDR value calculation and ISNT rule calculation will be included using image processing techniques to improve the process of glaucoma disease classification. Future work we will consider more number of images with different resolution, intensities as well as different diseases to make the system more efficient in the manner of accurate glaucoma disease prediction using recent technology.

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J. Jeslin Shanthamalar is currently pursuing her Ph.D programme at Department of Information Science and Technology, Anna University, Chennai, India. She did her Master Degree in Computer Science and Engineering from Jerusalem College of Engineering, affiliated to Anna University, Chennai in 2013. Her research interests include Image Processing, Machine Learning and Data Mining.

Dr. R. Geetha Ramani is currently working as a Professor at Department of Information Science and Technology, Anna University, Chennai, India. She has more than 20 years of teaching and research experience. Her areas of specialization include Data Mining, Evolutionary Algorithms, Network Security, Image Processing, Data Mining and Medical Image Analysis. She has also published a couple of books in the field of Data Mining. She has more than 100 publications in international journals, national journal and conference papers.