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SVM BASED CLASSIFICATION AND DETECTION OF GLAUCOMA USING OPTIC DISC AND OPTIC CUP SEGMENTATION

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ABSTRACT

This paper proposes a computer aided decision support system for an automated detection of glaucoma in monocular fundus images. Identification of Glaucoma using fundus images involves the measurement of the size, shape of the Optic cup and Neuroretinal rim. Optic Cup detection is a challenging task because of the interweavement of cup with the blood vessels. A new color model technique based on pallor in fundus images using K means clustering is proposed to differentiate between the Optic cup to disc boundary. The method differs by initial optic cup region detection followed by the erasure of blood vessels. In addition to the shape based features, textural features are extracted to better characterize the pathological subjects. The major problem in detection is that, there does not exist a great difference both in color and intensity, so segmentation and edge detection becomes tougher. This exact detection of optical disc and optical cup helps the doctors for easy detection of diseased based on retinal fundus images. So accuracy in finding the area becomes vital. Since glaucoma progresses with few signs or symptoms and the vision loss from glaucoma is irreversible, screening of people at high risk for the disease is vital. In this project, segmentation is done using adaptive mean shifting based region growing algorithm based edge detection. The proposed method is expected to have good accuracy. Optimal set of features selected by Genetic algorithm are fed as input to Adaptive Neuro fuzzy inference system for classification of images into normal, suspect and abnormal categories. The method has been evaluated on 550 images comprising normal and glaucomatous images. The performance of the proposed technique is compared with Neural Network and SVM Classifier in terms of classification accuracy and convergence time. Experimental results shows that the features used are clinically significant for the accurate detection of glaucoma.

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I INTRODUCTION

Glaucoma the leading cause of blindness and asymptomatic in the early stages and its detection is essential to prevent visual damage [1]. About 2% of the population between 40- 50 years old and 8% over 70 years old have elevated intraocular pressure (IOP) [2] which increases their risk of significant vision loss and blindness. Digital color fundus image has emerged as a preferred imaging modality for large scale eye screening programs due to its non-invasive nature. The less expensive fundus images are used in the proposed work rather than the expensive techniques such as Optical Coherence Tomography (OCT) and Heidelberg Retinal Tomography (HRT).

Optic Disc detection is an important issue in retinal image analysis as it is a significant landmark feature and its diameter is used as a reference for measuring distances and sizes. The optic disc and cup were located by identifying the area with the highest average variation in intensity among adjacent pixels [3]. Automatic detection of optic disc is performed by region of interest based segmentation and modified connected component labelling. Boundary tracing technique was applied to detect the exact contour of optic disc. A quantitative analysis is performed on the neuroretinal rim area to assess glaucoma. [4]. In this approach, a potential set of pixels belonging to cup region is first derived based on the reference color obtained from a manually selected point. Next, an ellipse is fit to this set of pixels to estimate the cup boundary. A variant of this method obtains the cup pixels via thresholding of the green color plane [5]. To handle large inter-image intensity variations that arise due to complex imaging, additional information such as small vessel bends ('kinks') which anatomically mark the cup boundary have been used in [6].A Deformable model was presented for the detection of Optic Disc and cup boundaries. The method improves snake model and is robust to edges and ill defined edges [7]. Optic disc is detected using local image information around each point of interest in a multi dimensional feature space. Optic cup is detected by making use of the vessel bends at the cup boundary. Bends in a vessel are detected using a region of support concept and a multistage strategy followed by a local spline fitting to find the desired cup boundary. The method captures OD boundary in a unified manner for both normal and challenging cases without imposing any shape constraint on the segmentation result. Segmentation results shows consistency in handling geometric and photometric variations found across the dataset [8].

A deformable model guided by regional statistics is used to detect the OD boundary. Cup boundary detection scheme is based on Lab color space and the expected cup symmetry. This method uses sector wise information and give rise to fewer false positives and hence better specificity. Error value computed is less for a normal image than for a glaucomatous image [9]. Optic disc and cup are extracted in order to determine cup to disc ratio. Optic disc is extracted using a variational level set method and the detected contour is uneven due to influence of blood vessels. Detection of cup boundary was performed using intensity and threshold level set approach. Thresholding techniques produced better results for both high and low risk retinal images. An ellipse fitting is used to smoothen the boundary [10, 11].

Cup to disc ratio was measured using a vertical profile on the optic disc on the blue channel of the color image to diagnose glaucoma. Sensitivity of 80% and a Specificity of 85% [12] were achieved using vertical CDR measurement for seventy nine images. An algorithm to detect glaucoma using mathematical morphology was developed using fundus images. Developed Neural network system identified glaucoma automatically with a sensitivity of 100% and specificity of 80% [13].A framework for the detection of glaucoma based on the changes in the optic nerve head using orthogonal decomposition method was used in [14].The changes in the optic nerve head were quantified using image correspondence measures namely L1 norm, L2 norm, correlation and image Euclidean distance. A novel cup segmentation method based on support vector clustering algorithm [15] is described for the purpose of supporting glaucoma diagnosing in ophthalmology. 30 geometric features were computed on the extracted cup region and the technique achieved 94.5% sensitivity and 97.5% specificity when trained with SVM classifier.3D images are generally not available at primary care centres due to their high cost. Therefore a solution built around these imaging equipments is not appropriate for large scale screening program. An automated classifier is developed based on adaptive neuro-fuzzy inference system (ANFIS) to differentiate between normal and glaucomatous eyes from the quantitative assessment of summary data reports of the Stratus optical coherence tomography (OCT) images. With stratus OCT parameters as input a good discrimination was achieved between the eyes [16]. A novel method [17] is proposed to detect glaucoma using a combination of texture and higher order spectral features from fundus images. Features extracted have a low p value and are clinically significant. An accuracy of more than 91% is obtained with a random forest classifier combined with z score normalization and feature selection methods. Most of the works related to Glaucoma detection based on fundus images concentrate only on the Cup to Disc Ratio (CDR).CDR was found to be inconsistent sometimes to detect Glaucoma since the patients may have severe visual loss with a small CDR as in Figure 1 and vice versa. Cup/disc ratio staging system does not account for disc size and that focal narrowing of the neuroretinal rim

present between the optic disc and optic cup is not adequately highlighted. So a method has been proposed to accurately detect Glaucoma based on CDR, Neuroretinal rim area to find the rim loss and textural features in order to detect pathological subjects correctly.

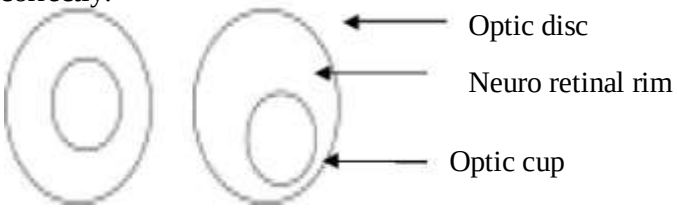


Figure 1. Optic nerve drawings with identical cup/disc ratios but with unequal rim width

II. MATERIALS USED

Fundus images used in this work are captured by Topcon TRC50 EX mydriatic fundus camera with a 50° field of view at Aravind Eye hospital, Madurai. The image size is 1900x1600 pixels at 24 bits true color image. Doctors in the ophthalmic department of the hospital approved the images for the research purpose.

III. PROPOSED METHOD

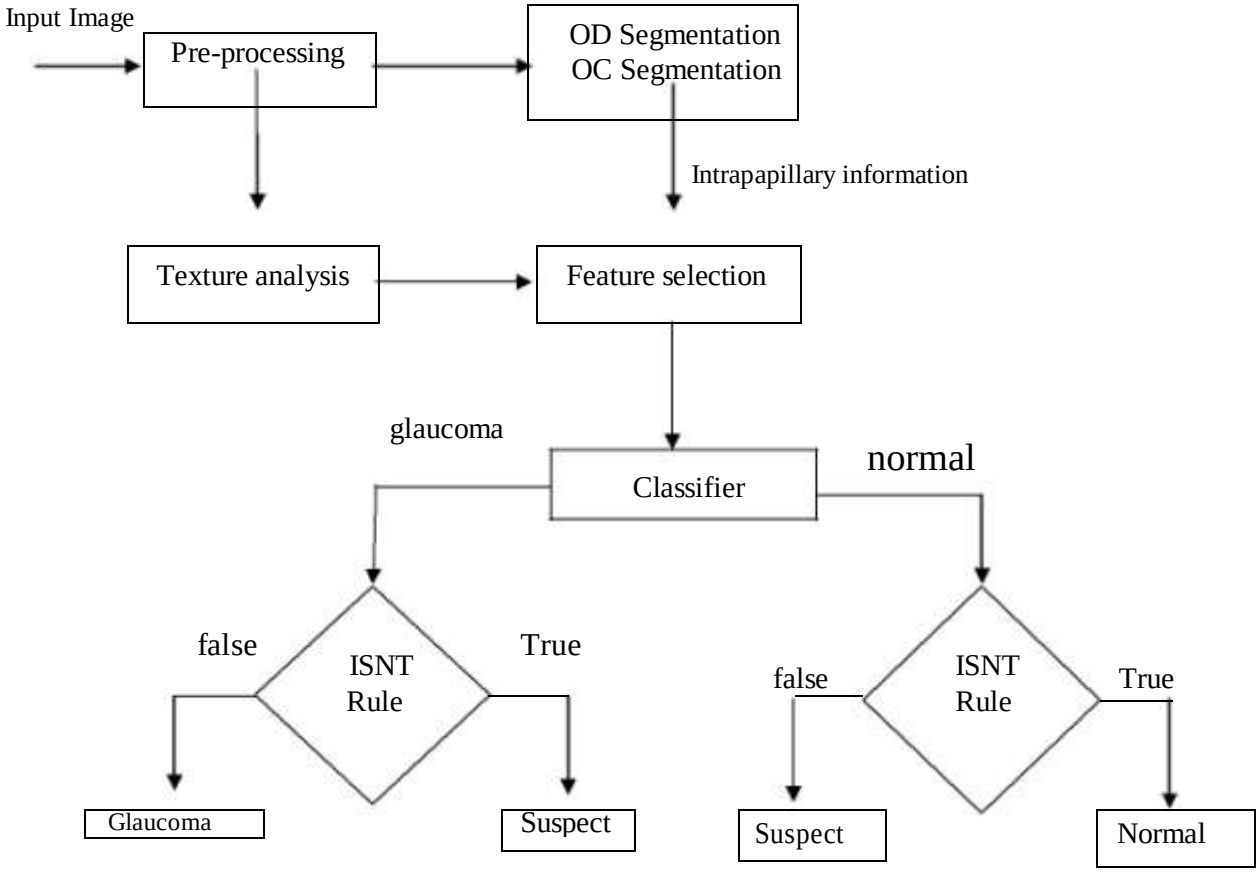


Figure 2. Flowchart of the proposed method

An efficient segmentation of optic disc and optic cup is essential to get a better localization of Neuroretinal rim area to diagnose various stages of glaucoma. As glaucoma progresses, the optic cup becomes larger and hence the cup to disc ratio is higher. Further the blood collects along the individual nerve fiber that radiate outwards from the nerve [17]. Such physiological changes are manifested in the fundus images and the experiments shows that the cup to disc ratio and texture features are able to quantify such difference in eye physiology.

3.1 Pre-processing

The flowchart of the proposed work is shown in Figure 2. RGB color retinal images are pre-processed using anisotropic diffusion filter in order to remove noise. The advantage of anisotropic diffusion [18] is that there is no need to know about the noise pattern or power spectrum previously and also it will provide better contrast while r emoving the noise. The filter iteratively uses diffusion equation in combination with information ab out the edges to preserve edges. The equation for anisotropic diffusion is defined as: $I\ div(\ c\ (*\ x\ ,y,\ t\ )I\ )=c\ (x,\ y,\ t\ )\quad I\ )\ +\ c\ .\ I$ (1)

where div is the divergence operator, is a gradient operator, c is the conduction coefficient function Anisotropic diffusion filtering i ntroduces a partial edge detection step into the f iltering process so as to encourage intra-region smoothing and preserve the inter-region edge. Aniso tropic diffusion is a scale space, adaptive technique which iteratively smoothes the images as the time *t* increases. The time *t* is considered as the sca le level and the original image is at the level 0. When the scale increases, the images become m ore blurred and contain more general information.

3.2 Detection of optic cup

Optic disc is detected using region of interest based segmentation and the bounding rectangle enclosing the region of interest is set as 1.5 times the disc width parameter. In this paper a new approach for the segmentation o f Optic cup is proposed. The proposed method shown in Figure 3 is aimed to detect the optic cup ex actly to calculate the Neuroretinal rim area pres ent between the disc and cup. Unlike most of the previous methods in the literature, proposed met hod differs by initial optic cup region detection follow ed by the erasure of blood vessels to get a highe r accuracy.

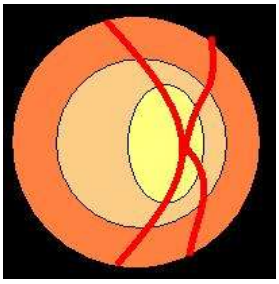


Figure 3. Systematic Representation of the color model

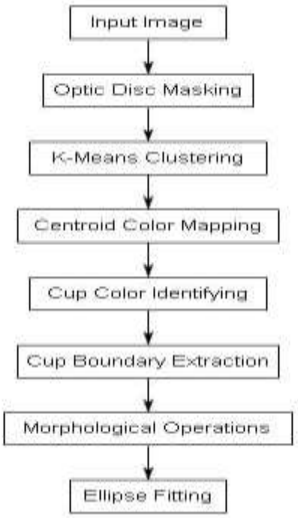


Fig ure 4. Flow Diagram of the proposed method

The optic cup and disc areas us ually differ in color, known as pallor. This method makes use of this difference in

pallor to delineate the cup-disc boundary. Observations on the reti nal images show that the actual cup pallor differs between different patients and even between imag es of the same retina due to changes in the lighting conditions. So the prior knowledge of color inten sity of the optic cup cannot be fixed.

Optic cup is detected using the technique proposed in Figure 4. In order to detect the optic cup region from the surrounding region, color space analysis, a segmentation algorithm based on histogram analysis and k means clustering followed by morphological operations has been developed. Since color space transformation plays a significant role in image processing, this step incorporates color information into the segmentation process, where the original RGB image is transformed to different color spaces and it has been found that L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All the color information is in the 'a*' and 'b*' layers. Optic cup is obtained clearly in this color space when compared with the other color spaces as shown in Figure [5]. These spaces serve as feature vectors for k means clustering. Color difference is measured using Euclidean distance metric.

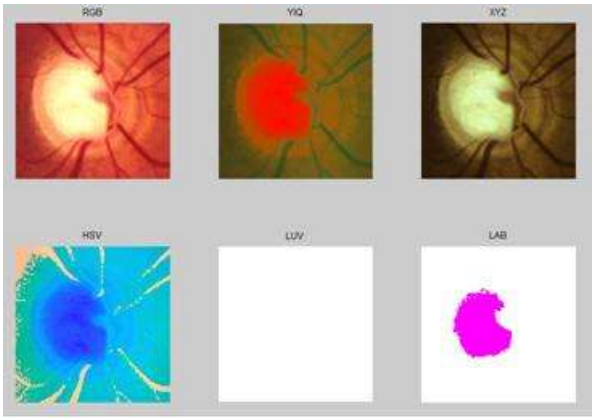


Figure 5. Color space conversion

In the proposed color model for the detection of optic cup, Optic disc consists of regions viz Optic cup, Interior Optic Disc, Exterior Optic Disc and Blood vessels. So the number of clusters is selected as four (K=4) manually using domain knowledge. Since the CIE L*a*b* feature space is three dimensional, each bin in the color histogram has N^d-1 neighbors where N is the total number of bins and d is the number of dimensions of the feature space. N is experimented for various values like 5, 10, 15 and the value of N is chosen as 10 by trial and error method and d is 3. Then the 3D colour Histogram is computed. The technique uses histogram information of 3 1D color components to find the number of valid classes. Disc is masked with a radius equal to greater than the size of the optic Disc. The masked image is fed to the clustering process in order to group the pixel values into regions. Number of clusters for k means clustering is determined automatically using Hill Climbing technique[19].Peaks are identified by comparing the pixels with the neighboring bins and the number of peaks obtained indicates the value of *K*, and the values of these bins form the initial seeds. The initial seeds for the algorithm was selected from local maximum of the 3D color histogram of the CIE L*a*b color space. These formed seeds are then passed to K mean clustering. K-Means is an unsupervised clustering algorithm [20] that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. K Means Clustering process is explained in the steps below

1. Number of clusters k is taken as four. Lower value of k leads to an increase in the cup size. Higher value results in the predominance of blood vessels. An incorrect value of k gives a sub optimal result.
2. Initialize cluster centres □1… □k .Choose k data points and set cluster centres to these points and make them as initial centroids. The data points are grouped into k clusters such that similar items are grouped together in the same cluster
3. For each data point, nearest centroid is found and the data point is assigned to the cluster associated with the nearest centroid. Centroid is the mean of the points in the cluster.
4. Update the centroid of each cluster based on the items in that cluster. The new centroid will be the mean of all points in the cluster.

For a given cluster assignment C of the data points, cluster means m_k is computed as in equation 2.

$$m_k = \frac{\sum_{i:C(i)=k} x_i}{N_k}, \quad k = 1,\mathrm{K}, K. \tag{2}$$

For a current set of cluster means, each observation is assigned as in equation 3.

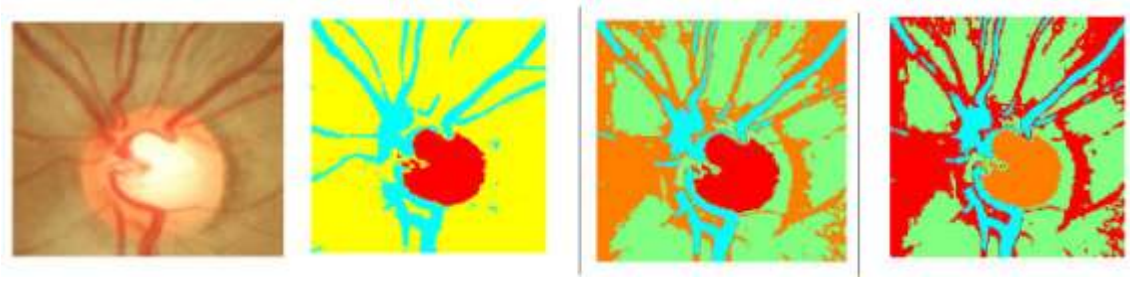
$$C(i) = \arg\min_{1 \le k \le K} \left| x_i - m_k \right|^2, \quad i = 1,\mathrm{K}, N \tag{3}$$

The centroid is taken and data is mapped to the closest one, using the absolute distance between them. 5. The above two steps are iterated until convergence and when there are no new re-assignments it is stopped.

K-means minimizes within-cluster point scatter shown in equation 4

$$W(C) = \frac{1}{2}\sum_{k=1}^{K}\sum_{C(i)=k}\sum_{C(j)=k} \left| x_i - x_j \right|^2 = \sum_{k=1}^{K} N_k \sum_{C(i)=k} \left| x_i - m_k \right|^2 \tag{4}$$

where x1,…, xn are data points or vectors or observations mk is the mean vector of the kth cluster Nk is the number of observations in kth cluster C(i) denotes cluster number for the ith observation. K-Means clustering groups the pixels within the Optic disc into the above mentioned four regions. Each cluster has a centroid. Then each region is filled with the corresponding region's centroid color. From these 4 regions, the region corresponding to optic cup can be easily identified by its centroid color. Each pixel within a cluster is then replaced by the corresponding cluster centre color. The brightest centroid color corresponds to the optic cup shown in Figure 6. Thus an initial boundary of optic cup is obtained. Pixels that are not classified are assigned to the closest cluster based on a weighted similarity measure between the clusters on the centre and the pixel in the image. L a* b* color space and k means clustering is more suitable to detect optic cup for normal and pathological subjects and exhibits a high Rand Index and lower Variation of Information (VoI), Global Consistency measure (GCM) and Boundary displacement (BDE) when compared with the other color spaces.



a b c d

Figure 6. a. Input Image b. clustered outputs for N =5 c. N=10 d. N=15

Boundary of the cup can be obtained using the equation by first eroding the image by the structuring element B and then performing the set difference between A and the eroded image.

$$\beta(A) = A - (A \Theta B) \tag{5}$$

The impact of blood vessel region within the cup is removed by morphological operations. This is performed by a dilation followed by erosion operation in the region of interest. A circular window of maximal vessel width as radius is used for dilation and erosion. A 3x3 structuring element is used in this work. Mathematically the functions are expressed using equations 6 and 7.

Dilation of the image A by B

$$A \oplus B = \{ P \in Z2 : P = a + b, a \in A \text{ and } b \in B \} \tag{6}$$

Erosion is defined by

$$A \Theta B = \{P \in Z2: P + b \in Z \text{ for every } b \in B\} \tag{7}$$

This step helps to reject outliers inside or outside the cup region and helps to get approximate cup region. Ellipse Fitting Algorithm based on least squares fitting algorithm is used to smooth the cup boundary. The modified optic cup boundary obtained is then fitted with ellipse as in Figure 7.Few sample results for diverse images are shown in

Figure 8 for optic cup boundary extraction and Neuroretinal rim area.

3.3 Feature Extraction

Transformation of images into its set of features is known as feature extraction. Features used in this work are based on intrapapillary and peripapillary information from the retinal images. Interpapillary parameters refers to the features extracted from optic disc and optic cup. Cup to disc ratio (CDR) and neuro retinal rim area to disc diameter are extracted from the segmented optic disc and optic cup. CDR was calculated by taking the ratio between the diameter of the Optic cup and disc in the vertical direction. CDR > 0.3 indicates glaucoma and CDR ≤ 0.3 is considered as normal. In glaucoma, structural changes in optic nerve head precede the functional changes. The conventional cup-disc ratio does not measure the actual rim loss which has a more diagnostic value in glaucoma. Neuroretinal rim tissue indirectly indicates the presence and progression of glaucomatous damage and it is related to the disc size. Neuro retinal rim area is calculated by subtracting the area of the optic cup from area of optic disc. Normally the rim is widest in the inferior temporal sector followed by the superior temporal sector, the nasal and the temporal horizontal sector. So Rim to Disc ratio used to estimate the width of the neuroretinal rim is considered as an important feature in the diagnosis of glaucoma. Texture analysis is performed in order to better characterize the abnormal images .Image diagnosis is based on the texture of the segmented portion of the image compared to that of the standard retinal texture image values. Texture extraction is the process of quantifying the texture patterns within a specified neighbourhood of size M by N pixels around a pixel of interest. Features are chosen in order to allow the discrimination between healthy and pathological subjects. The textural properties are derived by using first-order statistics and second-order statistics computed from spatial gray-level co-occurrence matrices (GLCM). GLCM is a second order measure as it includes the relationship between the neighbourhood pixels. For an image of size m x n, a second order statistical textural analysis is performed by constructing GLCM [21].The data is normalized and contains feature vectors computed around each pixel. The normalized feature vector contains altogether 12 features computed over the window size of 'n × n' pixel matrix. Texture analysis is used to estimate the peri papillary information. Normal, suspect and abnormal classes are represented using relevant and significant features to classify the input images. In order to avoid the problem of dimensionality, it is desirable to have a smaller feature set. Twelve features are used in this work among which two are extracted from the segmented optic disc and cup region and 10 are extracted from the texture analysis. Features used are cup to disc ratio, rim to disc ratio, mean, standard deviation, skewness, kurtosis, contrast, correlation, inverse difference moment, variance, energy and entropy.

3.4 Feature selection

Feature selection refers to the problem of dimensionality reduction of data which consists of large number of features initially. The objective is to choose optimal subsets of features from the image. The sequential forward floating selection (SFFS) algorithm [22] and Genetic algorithm was experimented individually to find the best feature set for classification. The algorithm employs a ''plus 1, take away r'' strategy. Features are added sequentially to an initially empty feature set but, at every iteration features are also removed if that improves performance. In this way ''nested'' groups of good features can be found.

Genetic algorithm was used to select the most significant features [23] characterizing the shape of the disc and cup region.Since Genetic algorithms are relatively insensitive to noise, they seem to be an excellent choice for the basis of a more robust feature selection strategy to improve the performance of classification system. In this work, each of the twelve features are represented by a chromosome (string of bits) with 12 genes (bits) corresponding to the number of feature s. An initial random population of chromosomes is f ormed to initiate the genetic optimization. A suitable fitness function is estimated for each individual. The fittest individuals are selected and the crosso ver and the mutation operations are performed to generate the new population. This process conti nues for a particular number of generations and finally the fittest chromosome is calculated based on the fitness function. Features with a bit value "1" are accepted and the features with the bit value of "0 " are rejected.

Feature set selected from Gene tic algorithm provides significant six features namely cup to disc ratio, rim to disc ratio, skewnes s, contrast, correlation and inverse difference moment. In addition to the six features selected by Genetic Algorithm kurtosis is another paramete r selected by SFFS algorithm. Each of the features is normalized between 0 to 1 and the weighted features are used for training and testing of instances.

3.5 Adaptive Neuro-Fuzzy I nference System as Classifier (ANFIS)

Adaptive Neuro Fuzzy Inferenc e Systems combines the learning capabilities of neural networks with the approximate reasoning of fuzzy inference algorithms. ANFIS uses a hybrid learning algorithm to identify the

membership functio n parameters of Sugeno type fuzzy inference sy stems. The aim is to develop ANFIS-based learning models to classify normal and abnormal images f rom fundus image to detect glaucoma. An adaptive n eural network is a network structure consisting of five layers and a number of nodes connected through directional links.

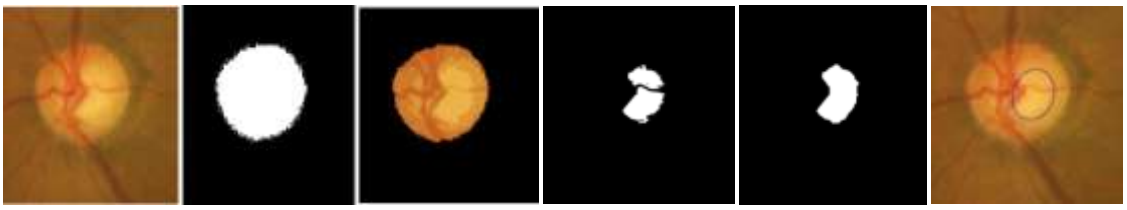
The first layer executes a fuzzification process, second layer executes the fuzz y AND of the antecedent part of the fuzzy rules, the third layer normalizes the fuzzy membership functions, the fourth layer executes the conseq uent part of the fuzzy rules and finally the last layer co mputes the output of the fuzzy system by summing up the outputs of the fourth layer [24].Each no de is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a Neural network is a process to determ ine parameter values to sufficiently fit the training dat a. Based on this observation, a hybrid-learning r ule is employed here, which combines the gradient de scent and the least-squares method to find a feas ible set of antecedent and consequent parameters.

In order to obtain a set of rules and avoid the problems inherent in grid partitio ning based clustering techniques, subtractive clusterin g is applied. This technique is employed since it allowed a scatter input-output space partitioning .The subtractive clustering is one-pass algorithm for estimating the number of clusters and the clust er centres through the training data. Parameters used for clustering are shown in Table 1.

Table 1. Parameters used for clustering

R ange of influence	0.5
S quash factor	1.25
A ccept ratio	0.5
R eject Ratio	0.15

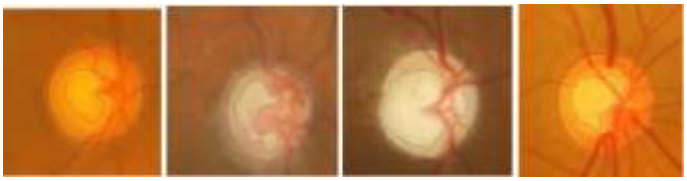
IV. EXPERIMENTAL R ESULTS



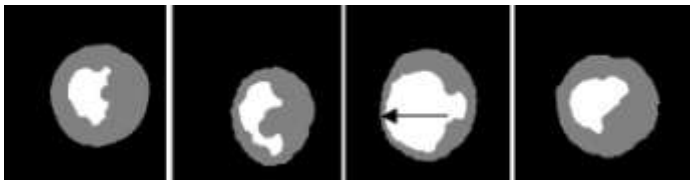
a b c d e f

Figure 7. Steps in the detection o f optic cup: a. Input image b. Mask image c. Color model d. Initial cup boundary e. Image smoothing f. Ellipse fitting.

(a)



(b)



(c)

Figure 8. Few sample results a) Input Images b) Cup boundary for the corresponding inputs c) Neuroretinal Rim area present between the disc and cup area shown in arrow mark

V. PERFORMANCE ANALYSIS

A) Optic cup detection

i) To assess the area overlap between the computed region and ground truth of the optic cup pixel wise precision and recall vales are computed

ii)

$$\text{Precision} = \frac{TP}{TP+FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (8)$$

where TP is the number of True positives, FP is the number of false positive and FN is the number of false negative pixels.

ii) Another method of evaluating the performance is using F Score given by

$$F = 2 * \frac{\text{Precision. Recall}}{\text{Precision + Recall}} \quad (9)$$

Value of F score lies between 0 – 1 and score will be high for an accurate method. Average F score for thresholdind and component analysis are compared and listed in Table 2.

Table 2. F score for cup segmentation

Images	Threshold	Component analysis	Proposed approach
1	0.67	0. 72	0.89
2	0.69	0.70	0.86
3	0.66	0.67	0.81
4	0.63	0.73	0.86
5	0.54	0.60	0.78
6	0.71	0.79	0.90
7	0.73	0.78	0.90
8	0.67	0.71	0.86
9	0.68	0.72	0.85
10	0.64	0.76	0.87

B) Performance analysis of the proposed technique

In the proposed system, six features are selected and hence the number of input variables is six. A sample of fuzzy if then rules is framed for fundus images classification. In a fundus image, Fuzzy if then rules form the input for the ANFIS architecture. ANFIS is initialized with 100 iterations and 0.001 step size value for parameter adaptation. Dataset used for fundus image classification is shown in Table 3.A 10 fold cross validation of data is used in the proposed work. From the available dataset, data is split into set1 and testing set. Next, set1 is further divided into training and validation set. Then the classifier is trained using training set and tested on validation set. The process is repeated by selecting various combinations of training and validation set. The classifier which gives best

performance is then selected and used to get performance in the testing set.

Table 3. Dataset for Fundus Image Classification

Images	Training Data	Test Data	No of Images/Class
Normal	50	130	180
Suspect	50	120	170
Abnormal	50	150	200
Total	150	400	550

In this work 150 images are used for training and 400images for testing. 150 images, 50 from each of the class for training and 400 images (130 normal, 120 suspect and 150 abnormal) for testing were used for classification. The schematic of the ANFIS structure obtained for the proposed system is shown in Figure9.

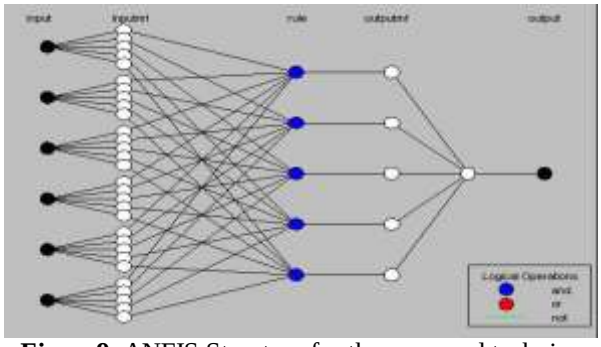


Figure9. ANFIS Structure for the proposed technique

Number of nodes used in the architecture is 79. 35 linear parameters and 60 nonlinear parameters are generated with 5 fuzzy rules. Root Mean square error is 0.022 when testing the data against the FIS structure. Classification accuracy is the ratio of the total number of correctly classified images to the total number of misclassified images. Table 4 shows the performance measure of the classifiers.

Table 4. Classification accuracy results of the classifier

Images	No of test images	ANFIS			Back		
		CCI	MI	CA(%)	CCI	MI	CA(%)
Normal	130	127	3	97.6	125	5	96.1
Suspect	120	119	1	99.1	117	3	97.7
Abnormal	150	149	1	99.3	147	3	98

CCI = Correctly Classified Images, MI = Misclassified Images, CA = Classification Accuracy

Performance of each classifier is measured in terms of sensitivity, specificity, and accuracy. Sensitivity is a measure that determines the probability of results that are true positive such that the person has glaucoma. Specificity is a measure that determines the true negatives that the person is not affected by glaucoma. Accuracy is a measure that determines the results that are accurately classified. The same dataset is used for neural network based Back propagation classifier. MATLAB (version 7.0) is used for implementation of the work. Comparative analysis performed between the classifiers based on correctly classified images, is shown in Table 5. Comparative performance of the classifier using the optimal feature subset selection is shown in Figure 10.

Table 5. Performance measure of the classifiers

Classifier	Specificity(%)	Sensitivity(%)	Accuracy(%)
ANFIS	97.6	99.2	98.7
BACKPROPAGATION	96.1	97.7	97.25

With Performance evaluation classification by means of Area under receiving operating characteristics (ROC), Classification with optimal feature selection achieves 0.99 A_Z, 0.0437standard error and 0.7427 computation seconds for ANFIS and 0.93 A_Z with 0.0123 standard error for Back propagation. Classification without optimal feature selection has 0.91 A_Z with 0.01405 standard error and 4.16 seconds for computation. Convergence time and RMSE of ANFIS is very less compared to Back Propagation Neural Network. ANFIS gives a good classification performance when compared
to back propagation in terms of convergence time and Root mean square error

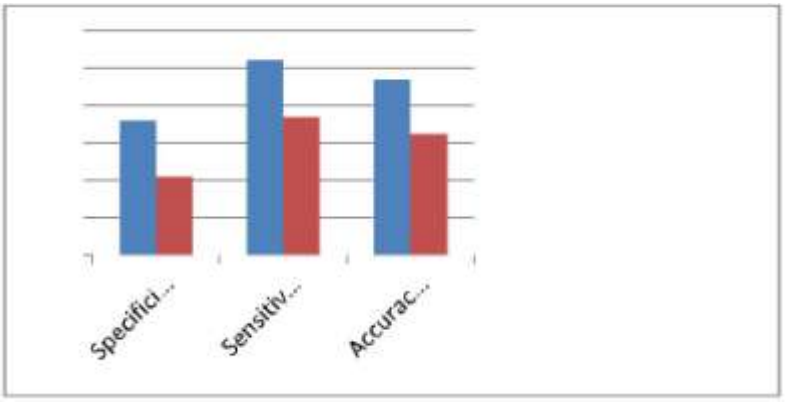


Figure 10. Comparative performance of the classifier

Impact of individual features on the detection of Glaucoma is given in Table 6. Textural features when with the shape characteristics namely rim to disc ratio and cup to disc ratio there was a good improvement in the accuracy. Graph showing the performance evaluation are shown in Figure11.

Table 6. Performance analysis of the features

Features	Sensitivity(%)	Specificity(%)	Accuracy(%)
Cup to Disc Ratio	93.5	95.3	94
Rim to Disc area	97	96.1	96.8
First order texture	92.5	89.2	91.5
Second order texture	95.1	90.7	93.7
CDR. RDR,	99.2	97.6	98.7
selective textural features			

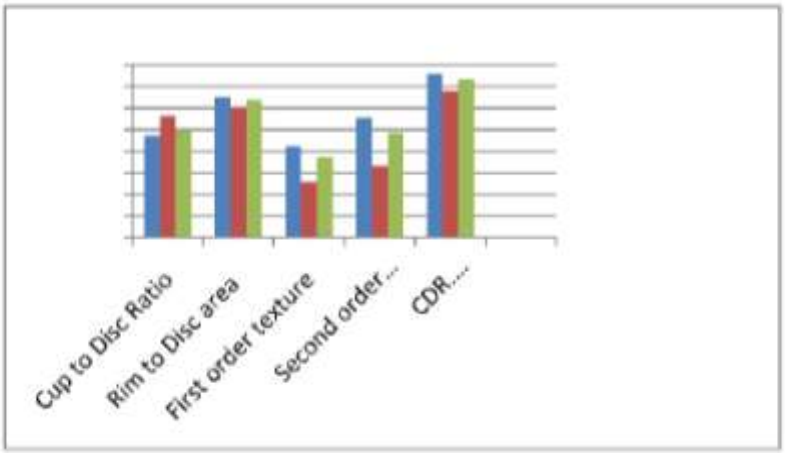


Figure 11.Performance measure of individual features.

VI. CONCLUSION

K Means clustering used in the proposed work focuses on the pallor information at each pixel thereby enabling rapid clustering and achieves a very good accuracy in detecting the optic cup. It is simple and easy to implement an unsupervised method rather than a supervised approach. Hill climbing technique and k means clustering provides a promising step for the accurate detection of optic cup boundary. Vertical CDR or superior or inferior rim area parameters may be more specific in identifying the neuroretinal rim loss along the optic disc compared to an overall cup-to-disc diameter ratio. Textural features are considered in this work in order to effectively detect glaucoma for the pathological subjects. A hybrid method involving textural features along with CDR, Neuroretinal Rim area calculation provides an efficient means to detect glaucoma. ANFIS achieves good classification accuracy with a smaller convergence time compared to Neural network classifiers. Performance of the proposed approach is comparable to human medical experts in detecting glaucoma. Proposed system combines feature extraction techniques with segmentation techniques for the diagnosis of the image as normal and abnormal. The method of considering the neuroretinal rim width for a given disc diameter with the textural features can be used as an additional feature for distinguishing between normal and glaucoma or glaucoma suspects .Progressive loss of neuroretinal rim tissue gives an accurate result to detect early stage of glaucoma with a high sensitivity and specificity. The proposed system can be integrated with the existing ophthalmologic tests, and clinical assessments in addition to other risk factors according to a determined clinical procedure and can be used in local health camps for effective screening.

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