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Detection Of Glaucoma Using Glcm And Mst Segmentation

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Abstract- Glaucoma is a globaleye disease that leads to blindness. This is the second leading cause of vision loss.If it left untreated the patient may lose vision, and even become blind.But blindness from glaucoma can often be prevented with early treatment. Existing Scanning methods like OCT, SLP, HRT has been used for detection of glaucoma but these methods do not identify glaucoma at early stage and also very expensive. Inmost conditions glaucoma gets developed and affects the vision of eye before its detection. In order to avoid this, Image processing techniques has been used for the detection of glaucoma. Image processing are increasingly used in various application such as medical imaging, remote sensing, film industry etc. This proposed work focused on medical image processing. Medical imaging is one of the most powerful tools for gaining insight into normal and pathological processes that affect health. Medical image processing is used for the detection of glaucoma by analyzing fundus images. In the proposed method, the fundus images have been preprocessed and the abnormal features have been extracted using HWT [Haar Wavelet Transform] and GLCM [grey level co-occurrence matrices]. The extracted features are segmented using minimum spanning tree and classified using SVM classifier. The system automatically detect the glaucoma disease of human eye accurately within a seconds from the given fundus image which eliminates the humanerror.

Keywords-Glaucoma, Haar Wavelet Transform(HWT),Grey Level CO-occurrence matrices[GLCM], Segmentation, Minimum Spanning Tree[MST],support vector machine [SVM].

I.INTRODUCTION

Glaucoma is a second leading cause of blindness. It is a chronic ocular disease which damages the optic nerve that leads to visual impairment and blindness. About eleven to sixty-seven million people have glaucoma globally. The disease affects about two million people in the United States. It occurs more commonly among older people. Closed-angle glaucoma is more common in women. The cause of glaucoma was not known easily and hence it has been called the "silent thief of sight" because the loss of vision usually occurs slowly over a long period of time. It is especially problematic because there are often no symptoms in its early stages. It is estimated that up to 50 percent of people with glaucoma don't realize they have it. The ophthalmoscope allowed people to see the optic nerve damage[8]. The optic nerve carries images from the retina, which is the specialized light sensing tissue, to brain so we cansee.

In glaucoma[4], eye pressure plays an important role in damaging the delicate nerve fibers of the optic nerve. At the 1st stage drainage canal gets blocked and buildup of fluid. This leads to the increase in IOP of blood vessels and optic nerve. Likewise glaucoma affects the eye slowly. The development of glaucoma is shown in fig 1.1. If the entire nerve is destroyed, then the blindness results. If glaucoma has been detected earlier and treated promptly then it can be controlled with no further vision loss. It is estimated that above six million peoples having glaucoma, about 5% of population between 40-50 years old and 10% over 70 years old, which increases the risk of significant vision loss[9]. Most people are not aware of such blind areas until the optic nerve has been destroyed substantiallyalready.

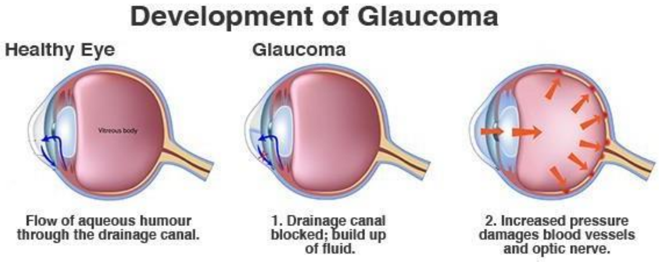


Fig 1.1 Development of Glaucoma

Many scanning methods like HRT (Heidelberg Retinal Tomography), SLP(Scanning laser polarimetry), OCT (Optical Coherence Tomography) are used to detect glaucoma[9]. The machines that are shown in fig 1.2 and 1.3 used for these scanning methods are so expensive cannot detect glaucoma at early stage and also requires experienced ophthalmologist to usethem.

Fig1.2OCT Fig 1.3 HRT

The image analysed here to find glaucoma was fundus image. The fundus image was taken using the fundus camera / ophthalmoscope. The fundus image of the eye shows the interior surface of the retina. So in order to detect glaucoma the fundus image of eye is needed. Both the normal and the abnormal fundus image will be sameas shown in fig
2.1. It is very much difficult to identify the affected eye. Human examination to identify it may cause errors. It requires experiences clinicians to examine the image, even though it cannot be identified at an earlystage.

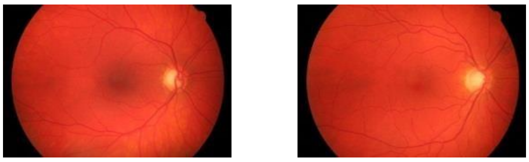
In order to avoid this, Image processing is used for analyzing the fundus image to detect glaucoma at an early stage. The 2-D fundus images undergo several preprocessing levels and followed by feature extraction. In this proposed work HWT [Haar Wavelet Transform] and GLCM [Grey Level co-occurrence Matrices] is applied for feature extraction of fundus images. Segmentation of fundus image using MST [Minimum Spanning Tree] is performed after the feature extraction process and SVM [Support Vector Machine] is adapted for classifying the glaucoma images with non-affected and affected. The key observation of this work is to detect glaucoma with accuracy at earlystage.

Here feature extraction and classification are the two central issues for automatic glaucoma recognisation. HWT and GLCM are used for extracting features of fundus image. The best extraction method undergoes classification in order to find the better extractors for the detection of glaucoma disease.

The rest of this paper is organised as follows: Database collection is discussed in section II. In sectionIII the proposed methodology and subsequent feature processing steps are discussed. Image segmentation and Classification are addressed in section IV. The results and discussion of the proposed method are presented in section V. The conclusions and future enhancement are described in section VI.

II. DATA USED

The digital retinal images were collected from the public database. It consists of 330 images including normal and glaucoma images. This database is obtained from the BIOMISA Research Group and is available online publicly at http://biomisa.org/glaucomadb/. These images are stored in JPEG file format at various resolutions.

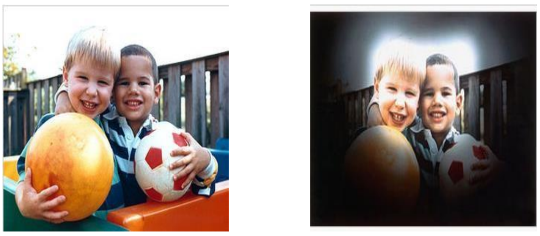


(A) (B)

Fig 2.1 Standard fundus image (A) Glaucoma eye image
(B) Normal eyeimage

III. PROPOSED METHODOLOGY

The main objective of this work is to detect glaucoma accurately at early stage by developing an algorithm which automatically analyze the eye fundus images and classify whether it is a normal or glaucoma affected eye. The difference between the normal eye vision and glaucoma eye vision has shown in fig3.1.



(A) (B)

Fig 3.1 Eye vision (A) normal eye vision
(B) glaucoma eyevision

This section presents the implementation methods for glaucoma detection. The architecture of our system with the several processing steps. The standard fundus image is taken as input to perform the preprocessing step for removing noise and improve the contrast of the image. After completing the pre-processing step, feature extraction is used for finding the abnormal retinal features using Haar and GLCM feature extraction methods. Segmentation process is carried out to segment the glaucoma affected region. Finally the segmented image undergoes classification for the detection of glaucoma. The image has been classified using SVMclassifier.

A. Pre-processing

The aim of image pre-processing is to improve data by enhancing some image features important for further processing. Random noise is usually present in medical images. This noise in the image can be reduced by using filters. Here the unknown retinal fundus image is taken as the input for preprocessing Stage. It undergoes several levels to convert as an enhanced image suitable for further process. Here the preprocessing levelsare,

- Gray scale conversion
- Noise reduction
- Histogram equalization
- Resizing
- Rescaling
- Top-hatfiltering

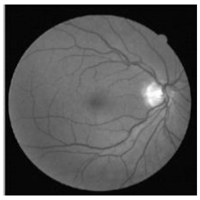
The retinal image is a RGB image so in order to extract the green channel from the retina. The fundus image has been converted to gray scale image. Here noise has been removed by using the inbuilt median filters in matlab. Thetop-hat filtering has been made in order to remove the negative region. The result of top-hat filtering is shown in black and white image. All images has been rescaled and resized to 500*500. Histogram equalization is also applied to remove the irregular illumination of image. The variations in theirpatterns are compensated by histogramequalization.

Gray scale conversion

Gray scale image is one of the simplest image enhancement techniques. The process of conversion of colour image (RGB) into a gray image is called gray scale conversion. The conversion of colour image to gray scale image has shown in fig 3.3. It can be performed using the followingfunction,
y=f(x) Where x: original input data; y: converted output data

A gray scale or grey scale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at thestrongest.

In order to extract the green channel image and noise reduction process from the RGB image, it has been converted to gray scale image.



(A) (B)
Fig 3.3 fundus image (A) RGB image
(B) Gray scaleimage

Colour digital images are made of pixels, and pixels are made of combinations of primary colours .In RGB colour model red color has more wavelength of all the three colors, and green is the color that has not only less wavelength then red color but also green is the color that gives more soothing effect to the eyes. It means that we have to decrease the contribution of red color, and increase the contribution of the green color, and put blue color contribution in between these two colours. Hence images in green bands shows fundus structures more reliably, so the green band was extracted.

Noise reduction

Noise reduction is the process of removing noise from a image. Images taken with both digital cameras and conventional film cameras will pick up noise from a variety of sources. Further use of these images will often require that the noise be removed. In order to get an enhanced image, noise canbeaddedmanually and removed. Insaltand pepper, pixels in the image are very different in color or intensity from their surrounding pixels. Generally this type of noise will only affect a small number of image pixels. In Gaussian noise, each pixel in the image will be changed from its original value by a smallamount.

To remove noise from the image many type of filters have been used. Here mean filters have been used to remove noise. A mean filter is a non-linear filter and if properly designed, is very good at preserving image detail. Median filters and others RCRS (rank-condition rank-selection) filters are good at removing salt and pepper noise from an image.

To run a median filter.

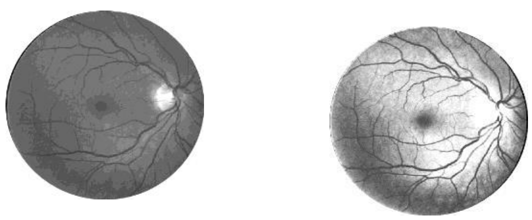
- Consider each pixel in theimage.
- Sort the neighboring pixels into order based upon their intensities.
- Replace the original value of the pixel with the median value from thelist.

Histogram Equalisation

Histogram conversion is the conversion of the histogram of the original image to another histogram. Histogram conversion can be said to be a type of gray scale conversion. There are two typical histogram conversion techniques,

- histogramequalization
- histogramnormalisation

In first step, an accumulated histogram should be made. Second, the accumulated histogram should be divided into a number of equal regions. Third the corresponding gray scale ineach region should be assigned to a converted gray scale. The effect of histogram equalization is that parts of the image with more frequency variation will be more enhanced, while parts of an image with less frequency will beneglected.



(A) (B)

Fig 3.4 (A) Gray image
(B) Histogram equalised image

Image editors have provisions to create an image histogram of the image being edited. The histogram of normal image is shown in fig 6.6. The histogram plots the number of pixels in the image (vertical axis) with a particular brightness value (horizontal axis). Algorithms in the digital editor allow the user to visually adjust the brightness value of each pixel and to dynamically display the results as adjustments are made.

Resizing/Rescaling

Images taken for analysis may be different in size; analysis of such images tends to be difficult and may leads to error in results. In order to avoid this resizing and rescaling have been done in pre-processing stage. Scaling refers to the resizing of a digital image. Image resizing is necessary when you need to increase or decrease the total number of pixels, whereas remapping can occur when you are correcting for lens distortion or rotating an image.

Top hat filtering

Indigital image processing, top-hat filtering is an operation that extracts small elements and details from given images. Here the negative regions of the retinal image has been removed using top hat filtering technique. Toph at filtering enhances the bright object in a dark background. For example: galaxy, it consists of small bright particles in dark background. These bright particles can be removed separately from the dark background of galaxy by using top hat filtering method.

B. Feature Selection/Extraction

A feature is nothing but the significant representative of an image which can be used for further segmentation and classification .Feature selection is the first step to get the feature extracted images. This method is very much helpful to the repeated feature and the selected feature which has no data. It will not choose without data, will not useful for future processing.

The selected feature has been extracted to simplifying the amount of resources requires to describe a large set of data accurately. Feature Extraction is a general term which depicts to extract only valuable information from given raw data. The main objective is represent raw image in its reduced form and also to reduce the original data set by measuring certain properties to make decision process easier for classification.

There are two types of texture features measure. They are first order and second order. In the first order, texture measures are statistics calculated from an individual pixel and do not consider pixel neighbor relationships. The intensity histogram and intensity features are first order calculation. In the second order, measures consider the relationship between neighbor relationships. The proposed method called “HWT” and “GLCM” is used for feature extraction.

HWT [Haar Wavelet Transform]

Nowadays the wavelet theorems make up very popular methods of image processing. Due to its low computing requirements, The Haar transform has been mainly used for

image processing and pattern recognition. It has efficient application due to their wavelet like structure.
To improve the accuracy, the efficient algorithm called “haar wavelet transform” is used for feature extraction. This method is applicable for different kinds of image extraction features. The decomposition process of haar transform has shown in fig 3.6

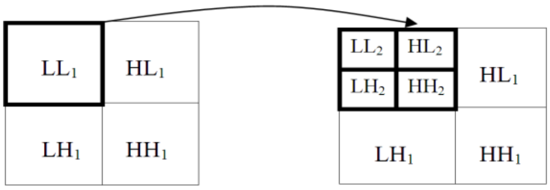


Fig 3.6 haar transformation

Haar Wavelet transform is used to calculate the feature vectors of textured images. Here it converts texture of retinal image to comparable mathematical characterization[14]. The image is decomposed to approximate components and detail components by 2-D wavelet function. The decomposition process by 2-D wavelet transform from the high scale to the low scale indicates approximate components. The decomposition of HWT is shown in fig 6.10, as HH, HL, LH (corresponding to , and) indicates detail components. The general form of decomposition haar transform is shown in fig 3.7 asfollows,

A	**H**
V	**D**

Fig 3.7General Form Of Haar Transform

A- (Approximation area) includes information about the global properties of analysed image. Removal of spectral coefficients from this area leads to the biggest distortion in originalimage.

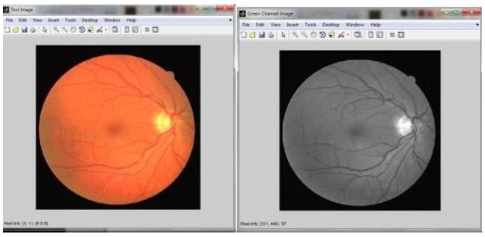
H- (Horizontal area) includes information about the vertical lines hidden in image. Removal of spectral coefficients from this area excludes horizontal details from originalimage.

V- (Vertical area) contains information about the horizontal lines hidden in Image. Removal of spectral coefficients from this area eliminates vertical details from originalimage.

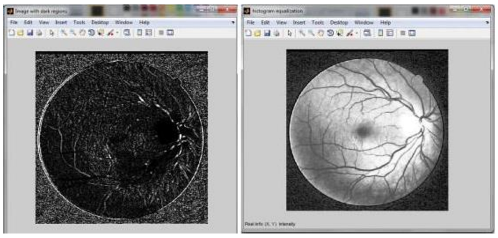
D- (Diagonal area) embraces information about the diagonal details hidden in image. Removal of spectral coefficients from this area leads to minimum distortions in originalimage.

Finally haar transform is composed of four coefficients such as A,H,V,D as shown above in fig. 3.7
.Thus the H,V,D coefficients are compared with the approximation coefficients value. Here the approximately assigned value is 0.003.so the feature that are more different

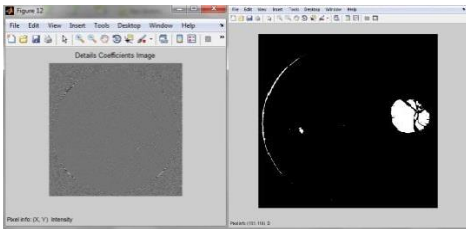
from the approximate features are get extracted for further process.



(A) (B)



(C) (D)



(E) (F)

Fig 3.8 (A) Input Image (B) Gray Scale Image
(C) top hat filtered image (D) Histogram Equalisation
(F) Feature Extraction (G) SegmentedImage.

GLCM [Grey Level Co-occurrence Matrix]

The proposed method called "GLCM" is used for feature extraction. The GLCM is a second order texture calculation. In this work, GLCM texture features are extracted from the given input image. A gray level co-occurrence matrix (GLCM) or co-occurrence distribution (less often co- occurrence matrix or co-occurrence distribution) is a matrix or distribution that is defined over an image to be the distribution of co-occurring values at a given offset. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image The use of statistical features is therefore one of the early methods proposed in the image processing literature. It considers the relationship between two neighbouring pixels, the first pixel is known as a reference and the second is known as a neighbour pixel. Given an image I, of size N×N, the co-occurrence, matrix P can be definedas:

N N
P(i,j) = Σ Σ1, if I (x,y) = I and I (x+Δx, y+ Δy)=j x=1 y=10, otherwise

Steps for GLCM:

Step 1: Read the command line from the users Step 2: Read the content of the image from .bmp file

Step 3: Calculate the co-occurrence matrix Step 4: Calculate Haralick texture features

Step 5: Save acquired information to a database file.
The Features that are extracted from the images are shown in Table I:

Moment	Formulae
Energy	$\mu = (1/MN) * \sum_{i=1} \sum_{j=1} p(i,j)$
Contrast	$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \right\}$, where $n = \lvert i-j \rvert$
Entropy	$f_3 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) log \left(p_{d,\theta}(i,j) \right)$
Correlation	$f_5 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y}$
Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$

Table I. GLCM Features

The Gray Level Co-occurrence Matrix (GLCM) method is used for extracting four Statistical Texture Parameters i.e., Entropy, Inverse Difference Moment, Angular Second Moment and Correlation. By extracting the features of an image by GLCM approach, the image compression time can be greatly reduced in the process of converting RGB to Gray level image when compared to other DWT Techniques. These features are useful in recognition applications like Military & Medical Applications.

IV. IMAGE SEGMENTATION AND CLASSIFICATION A. Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation[16] is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

The several approaches of image segmentation are

- Edge-based segmentation
- Region growing
- Region split and merge

- Watershedsegmentation
- Segmentation bymotion

Image segmentation is an important and challenging problem in image analysis in the field of machine vision for a unsupervised object based segmentation. Minimum spanning tree method is used as a proposed work for image segmentation.

MST is a undirected graph which contains all edges and vertex of the graph. It is also called shortest spanning tree which is the important concept of graph theory. Here MST algorithm is used for medical image segmentation. MST is a sub graph that compasses over all the vertices of a given diagram with no cycle and has least entirely of weight over all the induced edges. In MST based clustering ,the weight of every edge is considered as the Euclidean separation between the end focus framing the edge .Accordingly any edges that in faces two sub trees in the MST must be the briefest. In such grouping, routines, conflicting edges which are surprisingly more are expelled from MST. Basically MST has two types spanning tree algorithm. they are

- Prim'salgorithm
- Kruskal'salgorithm

Here kruskal'salgorithm[17] based minimum spanning tree is used for segmentation. First all small clusters are generated. In this method, which edges have minimum weight are connected and finally make a large cluster. After making this cluster edge inconsistency is applied to remove largest edge

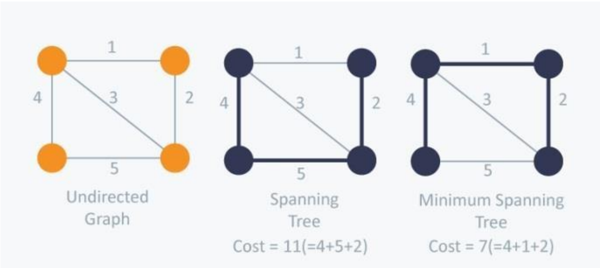
.

Fig 4.1 cost of MST

Minimum spanning tree is the spanning tree where the cost is minimum among all the spanning trees. It has been clearly shown in fig4.1.

Kruskal's algorithm

Kruskal's Algorithm builds the spanning tree by adding edges one by one into a growing spanning tree. Kruskal's algorithm follows greedy approach as in each iteration it finds edges which has least weight and add it to the growing spanning tree. Consider the following example given below in fig 4.2.

Algorithm Steps

- Sort the graph edges with respect to theirweights.
- Start adding edges to the MST from the edge with the smallest weight until the edge of the largestweight.
- Onlyaddedgeswhichdoesn'tformacycle,edgeswhich

connect only disconnected components.

In Kruskal’s algorithm, at each iterationwe will select the edge with the lowest weight. So, we will start with the lowest weighted edge first i.e., the edges with weight 1. After that we will select the second lowestweighted edge i.e., edge with weight 2. Notice these two edges are totally disjoint. Now, the next edge will be the third lowest weighted edge i.e., edge with weight 3, which connects the two disjoint pieces of the graph. Now, we are not allowed to pick the edge with weight 4, that will create a cycle and we can’t have any cycles. So we will select the fifth lowest weighted edge i.e., edge with weight 5. Now the other two edges will create cycles so we will ignore them. In the end, we end up with a minimum spanning tree with total cost 11 (= 1 + 2 + 3 +5).

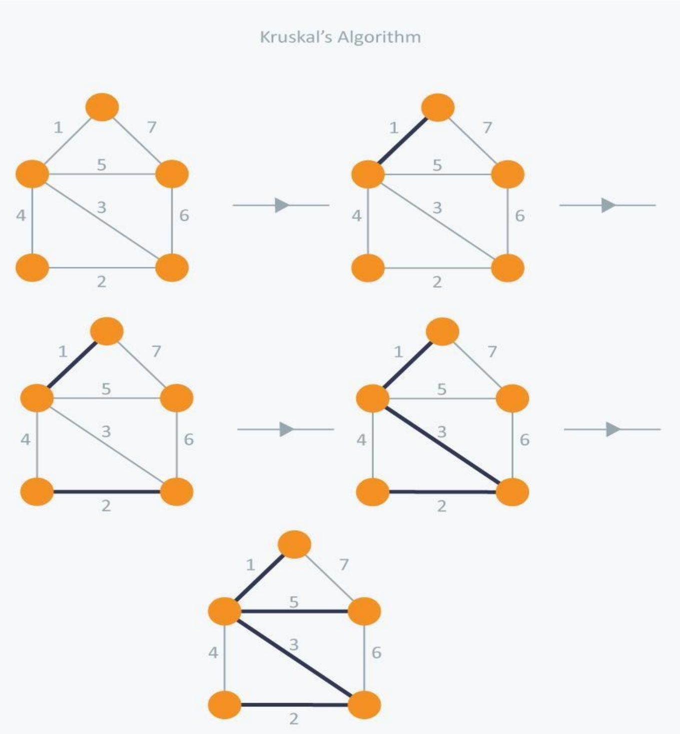
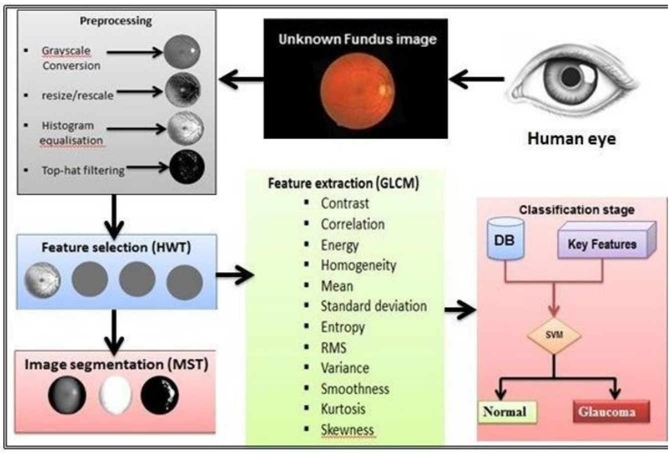


Fig 4.2 kruskal’s algorithm B .Image Classificatication

Classification refers to the analysis of the properties of an image depending upon the analysis. It is one of the most often used methods of information extraction they classifies the extracted features to identify the normal and abnormal images. These are done using classifiers. Usually multiple features are used for a set of pixels i.e., many images of a particular object are needed. Most of the information extraction techniques rely on analysis of the spectral reflectance properties of such imagery and employ special algorithms designed to perform various types of 'spectral analysis'. Experiments have been carried out to find the normal and the glaucoma image. Here SVM is used as classifier.



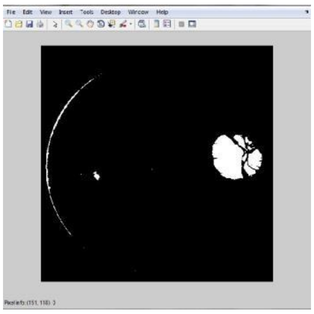


Fig 4.3 system architecture for detection of glaucoma

SVM (support vector machine)

SVM is among the best supervised learning algorithm for better classification. SVM[9] is based on the three big ideas. The first idea is minimizing the margin. This means that when we learn a linear separator we should try to choose the decision boundary so as to minimize the distance to the points that are closest to the boundary. The second idea is duality. This idea is used many times in optimization problems. It allows one problem to be transformed into another problem that may be easier to solve. The third big idea is kernels. This kernel allows a setof features to be mapped into a higher- dimensional and therefore more expressive feature space without incurring the full computational cost one might expect.The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output. The classification process is divided into the training phase and the testing phase. The known data is given in the training phase and unknown data is given in the testing phase. The accuracy depends on the efficiency of classification.

V. DISCUSSION

In our proposed methodology, the abnormal features are extracted using Haar and GLCM. The abnormal features undergo minimum spanning tree segmentation method. The segmented features undergo classification by using SVM classifier.

For the proposed work the fundus images were chosen randomly. Texture Features are obtained for the segmented part of the retinal image is shown in fig 5.1. GLCM features are extracted and its classification was obtained. From Table I, we observe the feature values for the various sampleimages.

Fig 5.1 segmented image

Feature	Img1 (normal)	Img2 (normal)	Img3 abnormal	Img4 abnormal
Energy	0.1453	0.1961	0.5936	0.7214
Contrast	0.1904	0.2661	0.7269	0.8175
Entropy	4.9486	5.0543	6.9135	7.4569
Correlation	2.2454	2.5357	3.9767	4.1253
Homogeneity	1.1227	1.2647	1.9835	2.0626

Table 1 Feature Extraction

From Table I, the images are classified as normal and abnormal using SVM Classifier. Also the graph shown in Fig
5.2 represents the statistical feature values for normal and abnormal images.

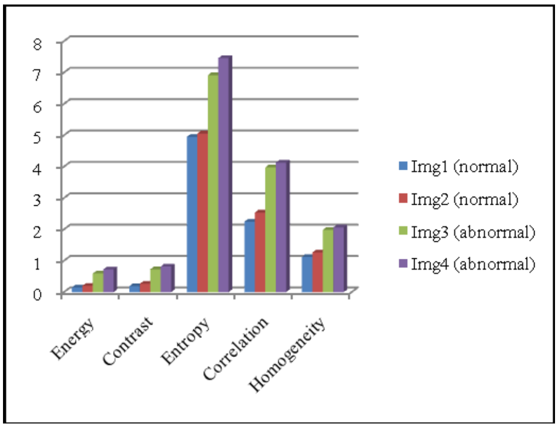


Fig 5.2 Performance Analysis

Different measures are used to evaluate the performance of the system. The measures used are Classification Accuracy (AC) and Mathews Correlation Coefficient (MCC). These values are calculated from the Confusion Matrix. A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The following table shows the confusion matrix for a two class classifier.

HWT-SVM	90%	83.3%	95%	80%

		Predicted	
		Negative	Positive
Actual	Negative	TN	FN
	Positive	FP	TP

Table 2 Confusion Matrix Predicted

TN (True Negative) – Correct Prediction as normal FN (False Negative) – Incorrect prediction of normal
FP (False Positive) – Incorrect prediction of abnormal
TP (True Positive) – Correct prediction of abnormal.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad \text{-------------} \quad 1$$

Table 3 Evaluation results

VI . CONCLUSION AND FUTURE ENHANCEMENT

In this paper, the accuracy obtained by GLCM is high when compared to the Haar transform extractor. The main reason is the low classification rate of haar extractions. GLCM is very efficient for feature extraction and they are very successfully used in biomedical image processing. Classification technique is developed to detect automatically whether glaucoma is present or not. The accuracy of the results obtained using SVM classifiers is 95% . The same idea can be extended to diagnosis of other diseases like diabetic retinopathy, fatty liver disease, thyroid cancer, and ovarian canceretc.

The Matthews correlation coefficient (MCC)is used in machine learning as a measure of the quality of binary (two-class) classifications. The MCC is in essence a correlation coefficient between the observed and predicted binary classifications; it returns a value between −1 and +1. A coefficient of +1 represents a perfect prediction, 0 no better than random prediction and −1 indicates total disagreement between prediction and observation. The MCC is calculated using:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad \text{---} \quad 2$$

Sensitivity and specificity are terms used to evaluate a clinical test. The sensitivity of a clinical test refers to the ability of the test to correctly identify those patients with the disease which is calculated from equation3.

Sensitivity: TP/(TP+FN) ---- 3

The specificity of a clinical test refers to the ability of the test to correctly identify those patients without the disease which is calculated from equation 4.

Specificity: TN / (TN+FP) 4

Accuracy, Mathews Correlation Coefficient, Sensitivity and Specificity are calculated using the values from Table III and equations 2,3,4 and 5. The evaluation results are obtained asfollows:

Feature	AC (%)	MCC (-1 to +1)	Sensitivity (%)	Specificity (%)
GLCM – SVM	95%	90.9%	100%	90%

REFERENCES

[1] B. Dashtbozorg, A. M. Mendonça, and A. Campilho,(2014)``Optic disc segmentation using the sliding band filter,'' Comput. Biol. Med., vol. 61, pp. 2112_2124.

[2] H.Fu,D.Xu,S.Lin,D.W.K.Wong,andJ.Liu,(2015) ``Automatic optic disc detection in OCT slices via low- rank reconstruction,'' IEEETrans.Biomed. Eng., vol. 62, no. 4, pp. 1151_1158.

[3] J. Cheng et al.,(2013) ``Superpixelclassi_cation based optic disc and optic cup segmentation for glaucoma screening,'' IEEE Trans. Med. Imag., vol. 32,no. 6, pp. 1019_1032,

[4] J. Nayak, U. R. Acharya, P. S. Bhat, N. Shetty, And T. C. Lim,(2009) "Automated Diagnosis Of Glaucoma Using Digital Fundus Images," IEEE Journal Of Medical Systems, vol. 33, No. 5, pp.337–346.

[5] M. C. V. S. Mary, E. B. Rajsingh, J. K. K. Jacob, D. Anandhi, U. Amato, and S. E. Selvan,(2014) ``An empirical study on optic disc segmentation using an active contour model,'' IEEE Biomed. Signal Process. Control, vol. 18, pp.19_29.

[6] M.Zavar, S.Rahati, M. R.Akbarzadeh-T, And H.Ghasemifard,(2011) "Evolutionary Model Selection In A Wavelet-Based Support Vector Machine For Automated Seizure Detection," Expert Systems With Applications, vol. 38, No. 9, pp. 10 751–10758.

[7] S. Dua, U. R. Acharya, P. Chowriappa, And S. V. Sree,(2012) "Wavelet Based Energy Features For Glaucomatous Image Classification," IEEE Transactions On Information Technology In Biomedicine,vol. 16,No.1 pp. 80–87.

[8] S.Youse_ et al.,(2014) ``Glaucoma progression detection using structural retinal nerve _berlayer measurements and functional visual _eld points,'' IEEE Trans. Med. Imag., vol. 61, no. 4, pp.1143_1154.

[9] ShishirMaheshwari, Ram BilasPachori, And U. RajendraAcharya,(2016) “Automated Diagnosis Of Glaucoma Using Empirical Wavelet Transform And Correntropy Features Extracted From Fundus Images”. IEEE Journal of Biomedical and Health Informatics,Issue:99,pp.1-1.

[10] SwamidossIssac Niwas, Weisi Lin, CheeKeongKwoh, C.-C. Jay Kuo,Chelvin C. Sng, Maria Cecilia Aquino, And Paul T. K. Chew (2016) “Cross-Examination For Angle-Closure Glaucoma Feature Detection” IEEE Journal Of Biomedical And Health Informatics, Vol. 20, No. 1.

[11] M.Vinay Kumar, SharadKulkarini (2012), “Tumors Classification using PNN Methods”,Volume-2, Issue- 5,International Journal of Soft Computing and Engineering (IJSCE), November 2012.

[12] Ali AsgharBeheshtiShirazi, Leila Nasseri,(2008) “Novel Algorithm to Classify Iris Image Based on Entropy by Using Neural Network”,International Conference on Advanced Computer Theory and Engineering,IEEE2008.

[13] Joes Staal, Michael D. Abràmoff, Meindert Niemeijer,MaxA. Viergever, , and Bram van Ginneken,(2004) “Ridge-Based Vessel Segmentation in Color Images of the Retina”IEEET ransactions On Medical Imaging, Vol. 23, No. 4, April2004.

[14] Zhu Wen yao1, Zhou jun2, WU Yu feng1 and Wang Ming jun,(2014) “ Iris Feature Extraction based on HaarWavelet Transform”International Journal of Security and Its Applications Vol.8, No.4 (2014),pp.265-272.

[15] Prof.N.D.Pergad, Ms. Kshitija V.Shingare(2015), “Brain MRI Image Classification Using Probabilistic Neural Network and Tumor Detection Using Image Segmentation”International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) Volume 4 Issue 6, June2015.

[16] S Sibi, SwarnaPriya R.M., Pranov Kumar, Raghavendra Singh, AnithaBaskar, (2013) , “Image Segmentation by Construction of Shortest Spanning Tree Using Prim’s Algorithm”International Journal of Scientific & Engineering Research, Volume 4, Issue 11, November- 2013.

[17] Ping WANG a, Zheng WEI a, *, WeihongCUI b, Zhiyong LIN b,(2016) “A Minimum Spanning Tree Based Method For UavImageSegmentation” Remote Sensing and Spatial Information Sciences, Volume III-7, 2016.

[18] Le Hoang Thai, Tran Son Hai,(2012) “Image Classification using Support VectorMachine and Artificial Neural Network”.I.J. Information Technology and Computer Science, 2012, 5,32-38.

[19] U. R. Acharya, S. Dua, X. Du, S. V. Sree, and C. K. Chua,(2011)“Automated diagnosis of glaucoma using texture and higher order spectra features,”IEEE Trans. Inf. Technol. Biomed., vol. 15, no. 3, pp. 449–455, May 2011.

[20] A. Pachiyappan, U. N. Das, T. V. S. P. Murthy, and R. Tatavarti, "Automated diagnosis of diabetic retinopathy and glaucoma using fundus and OCT images,"(2012)Lipids Health Disease, vol. 11, no. 73, pp. 1–10, 2012.

[21] M.Harshavardhan, S.Visweswara Rao, "Glcm Architecture For Image Extraction"(2014)International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE) Volume 3, Issue 1, January 2014.

[22]Mala Claro, Leonardo Santos, Wallinson Silva Fl_avioAra_ujo, Nayara Moura "Automatic Glaucoma Detection Based on Optic DiscSegmentation and Texture Feature Extraction"(2016)CLEI Electronic Journal, Volume19, Number 2, Paper 4, August 2016

[23] J. Sivaswamy, S. Krishnadas, G. Datt Joshi, M. Jain, S. Tabish, and A. Ujjwaft, \Drishtigs:"Retinal image dataset for optic nerve head (onh) segmentation,"(2014) IEEE International Symposium on Biomedical Imaging (ISBI), 11th, 2014, pp. 53{56.

[24] L. Y. T. Danny,"Computer based diagnosis of glaucoma using principal component analylis (pca): A comparative study," (2011)SIM University, School of Science and Technology, 2011.

[25] P. Mohanaiah*, P. Sathyanarayana*, L. GuruKumar,"Image Texture Feature Extraction Using GLCMApproach"(2013)International Journal of Scientific and Research Publications, Volume 3, Issue 5, May 2013 1 ISSN2250-3153.

[26] Mark J. J. P. van Grinsven*, Bram van Ginneken, Carel B. Hoyng, Thomas Theelen, and Clara I. Sánchez,"Fast Convolutional Neural Network Training UsingSelective Data Sampling: Application to HemorrhageDetection in Color Fundus Images" (2016)Ieee Transactions On Medical Imaging, Vol. 35, No. 5, May 2016.

[27] U. M. Akram and S. A. Khan, "Automated detection of dark and brightlesions in retinal images for early detection of diabetic retinopathy," (2012)J.Med. Syst., vol. 36, no. 5, pp. 3151–3162,2012.

[28] J. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, ``Ridge-based vessel segmentation in color images of the retina,''(2004)IEEE Trans. Med. Imag., vol. 23, no. 4, pp. 501_509,Apr. 2004.

[29] A. Pachiyappan, U. N. Das, T. V. S. P. Murthy, and R. Tatavarti, "Automated diagnosis of diabetic retinopathy and glaucoma using fundus and OCT images,"(2012)Lipids Health Disease, vol. 11, no. 73, pp. 1–10, 2012.

[30] A. Aquino, M. E. Gegundez-Arias, and D. Marin, "Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques," (2010)IEEE Trans. Med. Imag., vol. 29, no.11, pp.1860-1869, November 2010.