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Retinal Abnormality Detection

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Abstract **– Glaucoma is the diagnosis given to a group of ocular conditions that contribute to the loss of retinal nerve fibers with a corresponding loss of vision.Glaucoma is the major cause of blindness in people above the age of 40. The Intra Ocular Pressure (IOP) increases because of the malfunction of the drainage structure of the eyes leading to Glaucoma. In this paper three methods-Gray Level Difference Method using ANN classifier, Stochastic watershed method using SVM classifier and Pearson R Correlation Method are proposed, which automatically detect Glaucoma disease in the human eye from the fundus database images.**

Index Terms – GLDM Feature extraction, Stochastic Watershed, and Pearson R correlation .

I. INTRODUCTION

The Aqueous humour that is secreted by ciliary muscles has immunoglobulins that protect the eye against pathogens and also maintain the shape of the eye. As the total amount of fluid within the eye increases, so does the pressure, similar to over inflating a tire, which damage retinal nerve fibers and hence the optic nerve cannot carry images to the brain. Loss of peripheral vision is the earliest symptom. If left untreated the field of vision will continue to narrow leading to tunnel vision. If detected early, loss of vision can most often be prevented. Glaucoma can be hereditary and diabetic people have double risk of getting affected by it.

There are two main types of glaucoma:

1. *Open-angle glaucoma:* Also called wide-angle glaucoma, this is the most common type of glaucoma. The structures of the eye appear normal, but fluid in the eye does not flow properly through the drain of the eye, called the trabecular meshwork.
2. *Angle-closure glaucoma:* Also called acute or chronic angle-closure or narrow angle glaucoma, this type of glaucoma is less common in the West than in Asia. Poor drainage is caused because the angle between the iris and the cornea is too narrow and is physically blocked by the iris.

II. LITERATURE SURVEY

Literature Survey is one of the most important steps in the course of execution of a project. It reduces the duplication of work.
J. K. Kim and H. W. Park [1] proposed Texture-analysis methods that can be applied to detect clustered micro calcifications in digitized mammograms. The conventional texture-analysis methods, such as the spatial gray-level dependence method, the gray-level run-length method, and the gray-level difference method are compared. Textural features extracted by these methods are exploited to classify regions of interest (ROI's) into positive ROI's containing clustered microcalcifications and negative ROI's containing normal tissues. A three-layer backpropagation neural network is used as a classifier. The results of the neural network for the texture-analysis methods are evaluated by using a receiver operating-characteristics (ROC) analysis.
Andres Diaz, Sandra Morales [2] proposed an algorithm that uses anatomical characteristics such as the position of the vessels and the cup within the optic nerve. Using several color spaces and the Stochastic Watershed transformation, different characteristics of the optic nerve were analyzed in order to distinguish between a normal and a glaucomatous fundus. The specificity and sensitivity obtained by the proposed algorithm are 0.81 and 0.87 using Luv color space, which means considerable performance in diagnosis systems.
Nataraj A. Vijapur, R.Srinivasa Rao Kunte [3] proposed an algorithm for Glaucoma detection. Pearson-R coefficients corresponding to the eye fundus image are used as features. Segmentation algorithm is used to segment optic cup and disc and their respective vertical diameters are calculated to determine cup-to-disc ratio. These novel techniques resulted in an overall efficiency of 97%.

III. PROPOSED METHOD

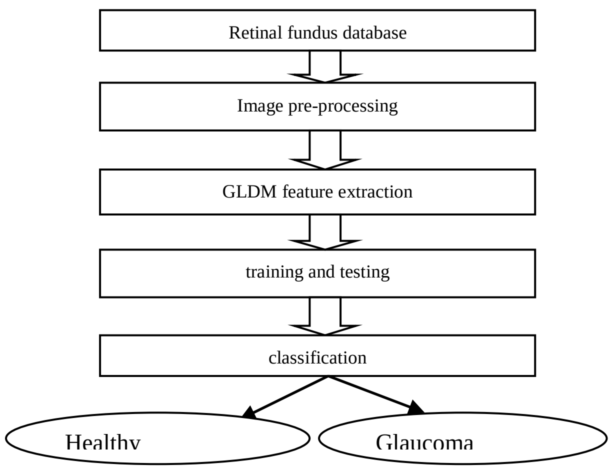

Figure 1. Proposed Methodology

This paper is mainly focused on finding the glaucoma disease using the fundus image. The proposed system automatically detects the normal or glaucoma affected image with very high accuracy using both statistical and training methods.

A. Retinal Fundus Database Collection

To develop the algorithm for automatic detection of glaucoma, the first essential step is to obtain the effective database and for that purpose retinal images were collected from Sushrutha Eye Hospital, Mysuru. The 2D fundus digital image is taken by a fundus camera, which photographs the retinal surface of the eye. In comparison with OCT/HRT machines, the fundus camera is easier to operate, less costly, and is able to assess multiple eye. Many researchers have utilized the fundus images to automatically analyze the optic disc structures.

B. Image Pre-Processing

It involves 3 operations

1. ***Image resize****:* The original fundus image is resized to 256×256 pixels which reduces the file size significantly without losing quality.
2. ***RGB to gray conversion:*** A grayscale image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information contrary to color image which has red, green and blue components.

Hence with Rgb to gray conversion we achieve ease of computation as complexity is reduced.

3. ***Contrast Enhancement:*** For better visualisation of retinal image details.

Image processing methods will remain same for all 3 methods.

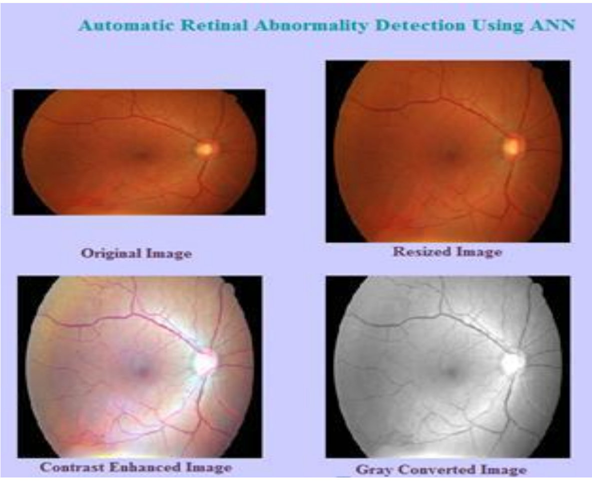

Figure 2. Image Pre-Processing

*C. **<u>METHOD 1</u>** - GLDM Featue Extraction using ANN classifier:*

Texture contains important information, which is used by humans for the interpretation and the analysis of several image types.

The Grey Level Difference Method (GLDM) is very powerful method for statistical texture description in medical imaging, Ultrasonic, MR and CT image analysis.

The GLDM is based on the given absolute difference in gray level between two pixels which are separated by a specific displacement δ.

- In this analysis, four possible forms of the vector d will be considered: (0, d), (-d, d), (d, 0), and (-d, -d) where 'd' is the inter sample spacing.
- I(m,n) , Image intensity function
- δ=(Δm,Δn) ,any displacement vector
- I'(m,n) = |I(m,n)-I(m+Δm,n+Δn)| is calculated for every displacement.
- g(.|δ) is estimated pdf of I'(m,n) which is calculated by counting no. of times each value of I'(m,n) occurs.
- Four probability density functions for four different displacement vectors d are obtained and the textural features are calculated for each of the 256 pixels giving 256×4=1024 texture features for each input image.

ANN: ANN is a group of interconnected nodes similar to the network of neurons in a brain.

It employs mathematical weights to decide the probability of input data. The weights are adjusted by training the network.

ANN Training:

There are generally 4 steps in training:

1) Assemble the training data.
2) Create the network object.
3) Train the network.
4) Simulate the network response to new inputs.

<u>METHOD 2</u> *– Stochastic watershed method:*

Watershed transformation is the segmentation technique developed for gray-scale images.

In this transformation, a given number M of marker-controlled watershed realizations are performed selecting N pseudo-random markers in each realization. The idea is to estimate a probability density function (pdf) for the contours of the image, which filter out non-significant border fluctuations. The probability density function is computed by window method as follows:

$$Pdf(X) = \frac{1}{M}\sum_{i=1}^{M}(WS_i(X) * G(X;s))$$

Where

$G(X;s)$ represents a Gaussian function of variance σ2 and mean μ(μ = 0), M= the sets of N regionalized random markers, WS_i = WS(g)$_{fmrki}$ the ith output watershed image, g= the gradient image.

Afterwards, it is necessary to perform a last marker- controlled watershed transformation on the pdf, which defines the resulting mask by joining all the watershed regions.

<u>METHOD 3</u>*- Pearson R Coeffecient Filter Method*

Pearson-R coefficients are the features which help further segmentation of optic cup and disc respectively. A correlation filter is designed, which matches the elements of the optic disc and cup structure. The correlation peak corresponds to brightest spot which is usually center of the optic cup. The template matrix consists of a Laplacian of

Gaussian with a vertical channel in the middle to correspond to the major vessel band. The template is correlated with the intensity component of the fundus image. The Pearson-R correlation, is used to account for variations in mean intensity defined by the equation

$$r = \frac{N\sum xy - (\sum x)(\sum y)}{\sqrt{[N\sum x^2 - (\sum x)^2][N\sum y^2 - (\sum y)^2]}}$$

These coefficients contain the information of optic cup and disc in the form of intensity variation with respect to template image from the fundus image.

Optic Disc and Optic Cup segmentation:

Here, the value of maximum value of the Pearson correlation filter is identified. The correlation coefficients are identified which satisfy the equality,

$r(i,j) \geq 0.75|FFT|max.$

Where,

|FFT|max is maximum value of the correlation coefficient.

In case of Optic cup the correlation coefficients are identified which satisfy the equality,

$r(i,j) \geq 0.85|FFT|max.$

From the segmented cup vertical diameter Vcup is calculated. Then, cup-to-disc ratio CDR is determined using the equation

$CDR = \frac{Vcup}{Vdisc}$

D. Classification

Classification is an important technique of image analysis which involves labeling of group of pixels based on the grey values or other statistical parameters. For understanding the contents of an image, image analysis functions are used.

Classification Using ANN :

A two layer back propagation network was employed for the classification of the disease. The network was trained using parameters of 30 patients. The training data was used to teach the network to classify the disease as Healthy, Glaucoma. Testing was done with parameters of 15 patients with glaucoma and 15 normal subjects including trained ones. Out of these 30 retinal images 26were identified correctly.

The proposed work achieved an accuracy (3) of 86.66% with sensitivity (1) at 93.33% and specificity (2) at 80%.This can be verified by analysing Table I.

$$Sensitivity = TPR = \frac{TP}{(TP+FN)} = \frac{14}{(14+1)} * 100 = 93.3\%$$

$$Specificity = TNR = \frac{TN}{(TH+FP)} = \frac{12}{(12+3)} * 100 = 80.0\%$$

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} = \frac{26}{30} * 100 = 86.6\%$$

Classification Using SVM:

SVM is designed to separate of a set of training images into two different classes, $(x_1, y_1), (x_2,y_2),\ldots(x_n, y_n)$ where x_i in R_d, d-dimensional feature space, and y_i in {-1,+1}, the class label, with i=1..n.

SVM builds the optimal separating hyper planes based on RBF kernel function (K). All images, of which feature vector lies on one side of the hyper plane, belong to class -1 and the others are belong to class +1.

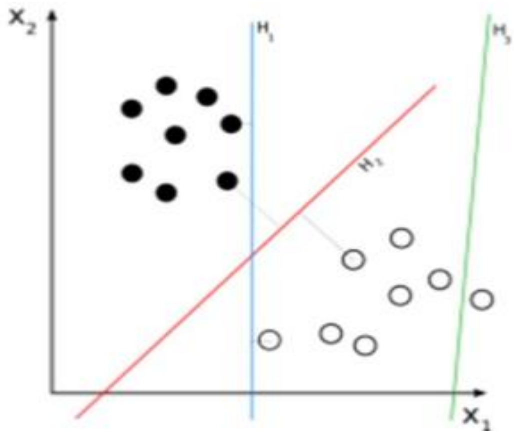

Figure 3:Separating hyper planes between two classes.

Classification Using Statistical Method:

$$pc = \frac{Covariance}{Standard\ deviation}$$

Where pc= Pearson Coeffecinet, If pc<5 Glaucoma is found and if pc>5 Fundus is Healthy.

IV. RESULTS

Retinal abnormality detection is performed using Artificial Neural Network and the results are as depicted below.

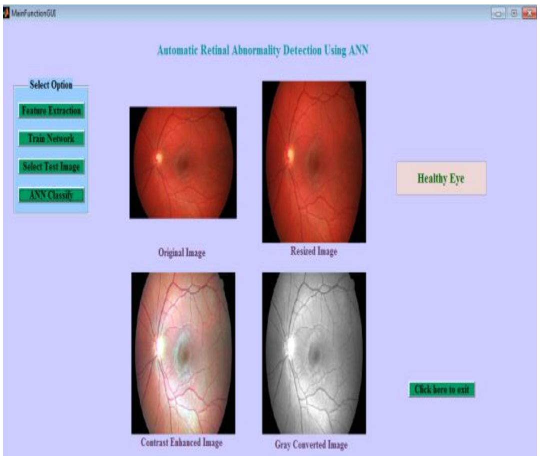

Figure 4. ANN Classification for Helathy Eye

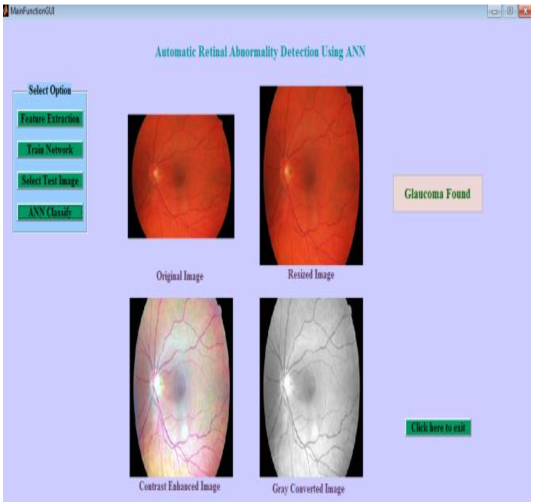

Figure 5. ANN Classification for Glaucoma Affected Eye

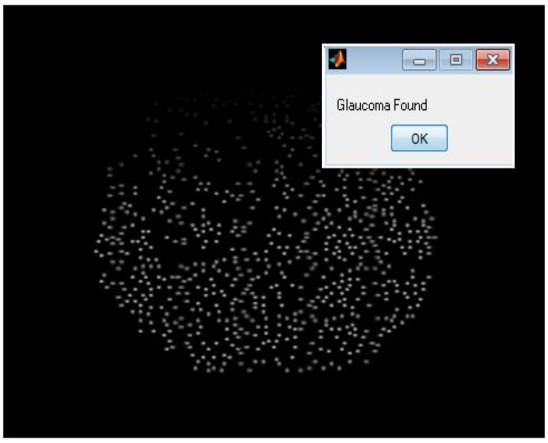

Figure 6. Stochastic watershed output

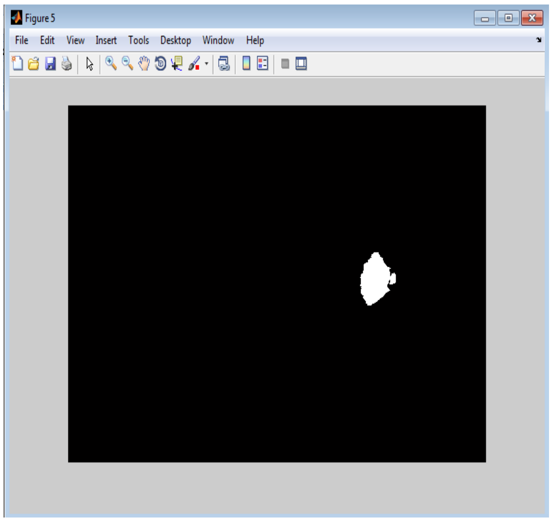

Figure 7. Segmented Disc area

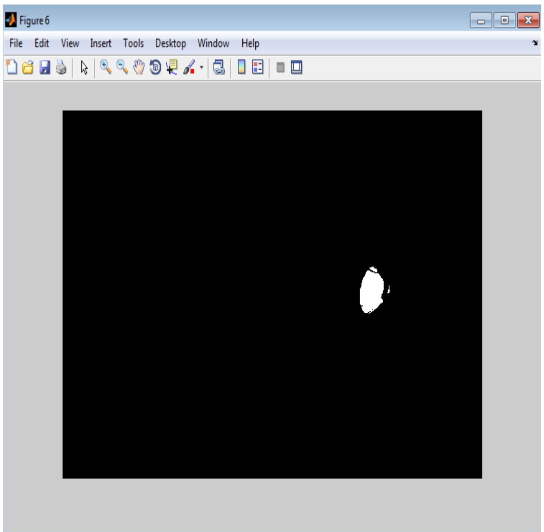

Figure 8. Segmented cup area

V. CONCLUSION

Glaucoma is caused due to the increased pressure within eye ball leading to the loss of vision. A comparative study of three methods-Gray Level Difference Method using ANN classifier, Stochastic watershed method using SVM classifier and Pearson R Correlation Method is done to detect Glaucoma disease in the human eye from the fundus database images. Here Matlab is used for training and simulating network to detect the presence of glaucoma.

The various parameters are easily extracted using Matlab and compared with standard values.

It can be concluded that trained networks perform better than statistical method. To make this more user friendly graphical user interface is also given which makes the handling of this tool very simple

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